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SOMMARIO

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Michele Gallo[1], Enrico Ciavolino

MULTIVARIATE STATISTICAL APPROACHES FOR CUSTOMER SATISFACTION INTO THE TRANSPORTATION SECTOR

Abstract:

The aim of this paper is to study the effect of the dimensions of the transportation service on the Passenger Satisfaction (PS) taking into account the spatial effect due to the interaction across spatial units and spatial heterogeneity. The relationships between the service dimensions and PS are formalized by a Structural Equation Model (SEM) based on the Partial Least Squares (PLS) estimation method which includes the spatial effects in the measurement model. Moreover, in order to get a 'true' measure of satisfaction, the rating scale model is proposed.

JEL classification: C13; C51

Keywords: Latent trait; Rating Scale Model; Spatial Structural Equation Models; Partial Least Squares

1. Introduction

The customer satisfaction survey gives important sources of information for quality assurance in many economic sectors, where the customer satisfaction is a vital concern for companies and organizations in their efforts to improve service quality, and maintenance of customer loyalty. However, customer satisfaction cannot be measured by simple statistical tools. It is a result of a latent complex information process summarized in a multiple-items questionnaire, in which one set of alternative responses is used for estimating probabilities of responses. For this reason, in the analysis of multi-item data the multidimensional

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nature of customer satisfaction and the different nature of the data should be considered (Gallo, 2007). In the public transport sector, the measurement of customer satisfaction (hereafter referred as passenger satisfaction) might be influenced not only by the particular features of the transport sector, but also by some spatial effects attributable to the territorial dislocation of stations.

Consider the spatial effect into passenger satisfaction model present two reasons. First it is expected that the spatial effect of socio-demographic, economic or regional activity may be an important aspect of a modeling problem. Second one the observations associated with spatial units might reflect measurement error (Le Sage, 1999).

Following Papalia *et al.* (2008) and Ciavolino *et al.* (2009) a new strategy which accounts for the spatial effect into PS analysis is proposed, including, as in a unique process of analysis, the Rating Scale Model (Gallo, 2009).

The paper framework is based on three steps. First, a particular version of Rasch Analysis called rating scale model (Andrich, 1978) is used to get a 'true' measure of satisfaction. Second differential item functioning and the spatial dimension is used to build the structural equation model. Latter partial least squares algorithm is proposed to estimate which component has more influence on the passenger satisfaction.

2. Theory

The Rating Scale model and the PLS are presented in the next sections, in order to show the potentialities and the main characteristics of both of them in the framework of the Passenger Satisfaction.

2.1 Rating Scale Model (RASCH ANALYSIS)

More latent trait models could be used to measure passenger satisfaction, but Rasch models are distinguished from others by a fundamental statistical characteristic - subject sum score is a 'sufficient statistic' for the underlying unidimensional latent trait (Wright and Linacre, 1989). The model is based on the simple idea that passengers who have a high total score on an item are more satisfied overall than passengers with low scores. Likewise, items that receive lower ratings are more difficult to endorse than items that receive higher ratings. This way, on a single continuum of interest, it is possible to clearly identify which items are more difficult to generate satisfaction and which passengers are more satisfied than others.

When all items present the same set of alternatives, it seems reasonable to expect that the relative difficulties of the steps between categories should not vary from item to item. For these kinds of questionnaires the rating scale is the more appropriate version of Rasch models. Rating Scale Model – within a probabilistic framework – converts ordinal raw-score data, such as the scale strong dissatisfaction / dissatisfaction / satisfaction / strong satisfaction, into an interval-based measure, the log-odd metric or logit. Let $P_{ij(s)}$ be passenger *i*'s probability of scoring *s* on item *j*, the rating scale model can be written:

$$P_{ij(s)} = \frac{\exp\left(x_i - \phi_j - \gamma_s\right)}{\left[1 + \exp\left(x_i - \phi_j - \gamma_s\right)\right]} \tag{1}$$

where ϕ_j is the difficulty for item j to generate satisfaction, x_i is the attitude of the i-th passenger to be satisfied, and γ_s is the threshold parameter associated with the transition between response categories *s*-1 to *s*.

To estimate these parameters, the "Joint Maximum Likelihood Estimation" algorithm is used in this paper (Wright et al., 1969). This method is more flexible and it is independent from specific passenger and item distributional forms. Moreover the logits measure $\ln\left(P_{ij(s)} \big/ \left(1 - P_{ij(s)}\right)\right)$ of the items, passengers and rating scale categories, convert ordinal raw scores into linear interval measures.

One important part of the item analysis is to examine Differential Item Functioning (DIF) in the items. DIF refers to differences in item functioning after groups have been matched with respect to ability or attribute that the item purportedly measures. Where DIF shows a difference between the groups of passengers, it does not mean that there exists measurement bias since it might be a real difference in satisfaction level. In these cases, DIF measure can be used instead of the passenger one to study the different level of satisfaction between the groups.

2.2 Spatial Structural Equation Model (S-SEM)

The Partial Least Squares (PLS) estimation method was first formalized by Herman Wold (1966, 1973), for the use in multivariate analysis. The application in Structural Equation Modelling (SEM) was again developed by Wold (1975) and the main references on the PLS algorithm are Wold (1982, 1985). The main idea of PLS for the SEMs is an iterative combination of path analysis to give a measure of the relationships among the theoretical constructs (*Structural Model* or *Inner Model*, equation 2), then factorial analysis for measuring the latent construct (*Measurement Model* or *Outer Model*, equation 3):

$$\xi_{(m,1)} = \mathrm{B}_{(m,m)} \bullet \xi_{(m,1)} + \tau_{(m,1)} \qquad (2)$$

$$\mathrm{x}_{(q,1)} = \Lambda_{(q,m)} \bullet \xi_{(m,1)} + \delta_{(q,1)} \qquad (3)$$

In the *Structural Model*, equation (2), $\boldsymbol{\xi}$ is the vector of the m latent variables and $\mathbf{B}$ is the path coefficients matrix, with zeros on its diagonal representing the causal effect among the latent variables. The *Measurement Model*, equation (3), contains the $\mathbf{x}$ vector of the q manifest variables and the coefficient matrices $\boldsymbol{\Lambda}$ of the relationships between the latent constructs and the observed variables. The vectors $\boldsymbol{\tau}$ and $\boldsymbol{\delta}$ are the structural and the measurement error vectors and the $\boldsymbol{\Psi}$ and $\boldsymbol{\Theta}^{\delta}$ are respectively the diagonal matrix variance of the structural error term $\boldsymbol{\tau}$ and the measurement error term $\boldsymbol{\delta}$.

Since we are observing H different units located in different positions, we have to take into account the effects which the geographic position can generate into the model. Spatial structures are generally associated to: a) *Absolute location* effects which are relevant to evaluate - for each observation - the impact of being located at a particular point in space, and to b) *Relative location* effects that consider relevant the position of an observation relative to other observations. The first effect called *spatial heterogeneity* assumes that each observation can have its own characteristic for the phenomenon under investigation. Moreover, in the latter case, it is assumed that the value observed in a sample in a specific location h can be affected by the value observed in another location k, with $h \neq k$. This effect, called *spatial dependence*, is due to the spatial interaction between contiguous observations.

The SEM formulation is therefore extended to take into account the spatial heterogeneity and the spatial dependence. The *spatial unobserved heterogeneity among* spatial observations is allowed by introducing fixed effects in the measurement model (Bernardini Papalia 2006, 2008a,b). We proceed by including an individual specific "dummy variable" to capture unobserved heterogeneity for each spatial observation h (h=1,…, H).

For the *spatial dependence*, we focus on one of the widely used approaches (called *spatial LAG model*) where the spatial correlation pertains to the dependent variable. In this context, it is assumed interdependence of latent variables across areas. This assumption may be formalized by including a spatial lag variable into the measurement model which represent the relationship between the manifest and latent variables. In doing this, a spatial weights matrix $\mathbf{W}$ of non-stochastic time constant weights has to be specified. This is a ($H \times H$) matrix in which the rows and columns correspond to the cross-sectional locations.

An element w_{hk} of the matrix expresses the prior strength of the interaction between location h (in the row of the matrix) and location k (columns). This can be interpreted as the presence and strength of a link between nodes in a network representation that matches the spatial weights structure. In most applications, the choice is driven by geographic criteria, such as contiguity (sharing a common border) or distance, including nearest neighbor distance (Anselin 1988; Lesage and Pace 2004).

More specifically, using the equation (3), the set of latent exogenous variables $\boldsymbol{\xi}$ is enlarged to include: *(i) Spatial Lag variable* (4), that is the first-order contiguity spatially lagged dependent variable; the *fixed effect*, that is the location dummy reported in equations (5); (iii) the set of q exogenous manifest variables $X_{H,q}$.

$$\mathbf{w}^{x} = Spatial - Lag = \mathbf{W}_{H,H} \cdot \mathbf{x}_{H,1} \tag{4}$$

$$\mathbf{d}^{s} = Dummy - Space = \mathbf{I}_{H,H} \tag{5}$$

To take into account the spatial lag variable and the fixed effect, the manifest variables of the equation (3) are rewritten as follow:

$$\mathbf{X}^*_{H,q+1+H} = \left[\mathbf{X}_{H,q} \mid \mathbf{W}_{H,H} \cdot \mathbf{x}_{H,1} \mid \mathbf{I}_{H,H}\right] \tag{6}$$

The equation (6) reports the specification of the locations in the measurement model, where, the vector $\mathbf{x}_{q,1}$ of the q manifest exogenous variables, is expressed in the form of matrix $\mathbf{X}_{H,q}$, with the locations reported in the rows and the variables in the columns. The matrix $\mathbf{I}_{H,H}$ is the identity matrix for the H locations.

The associated $\boldsymbol{\Lambda}$ matrix, which specifies the regression coefficients of the observed variables on the latent variables, is defined as $\boldsymbol{\Lambda} = [\boldsymbol{\tau} \mid \rho \mid \alpha]$, including: the set of the *manifest variables coefficients* ($\boldsymbol{\tau}$), the *spatial autoregressive parameter* (ρ) and the coefficient of the *spatial effects*.

The matrix formulation of the exogenous measurement model, equation (4), can be reformulated considering the spatial and the fixed effects, as below reported:

$$x_{q+1+H,1} = \hat{\imath}_{q+1+H,n} \bullet \xi_{n,1} + \delta_{q+1+H,1} \tag{7}$$

The measurement model is extended in this way adding to the q manifest exogenous variables, the spatial lag variable and the spatial effect, that means 1+H rows. In the estimation of a S-SEM, it is then essential to deal with the problem of endogeneity of the spatial lag term originated by the correlation between latent endogenous and exogenous variables and, as a consequence, the correlation between exogenous observed variables and errors. Our proposal is to use the PLS, which can be a powerful estimation method of analysis in case of small sample size, strong correlation among the items, missing data and no residual distribution assumption.

3. The measure of Passenger Satisfaction

To measure the passenger satisfaction a survey analysis was conducted on 2,473 passengers. The questionnaires were submitted by 10 different interviewers in the second week of October according to stratified random samples. Nine items (‘station cleanness’, ‘train cleanness', 'passenger comfort', 'regularity of service', 'frequency of service', 'staff behavior', 'passenger information', 'safety', 'personal and financial security') are used where each item has a Likert scale with four ordinal levels (Likert scale), viz., 'strong dissatisfaction' / 'dissatisfaction' / 'satisfaction' / 'strong satisfaction'.

The analysis of the Passenger Satisfaction consists of two parts: in the *first part*, the Rasch analysis is used to focus on the psychometric properties of the items, passengers, and rating scale categories. When the Rash diagnostic results guarantee the passenger satisfaction measure in terms of validity and reliability, the DIF measures were used to obtain the items measure for each station. The WINSTEPS program (Linacre and Wright, 2000) was used to obtain the results from these data.

To measure the relationships among the several aspects of passenger satisfaction, in the *second part*, a SEM is defined by considering three latent variables, *'Transportation'*, *'Information & Security'* and *'Comfort & Cleaness'*, which explain the *Passenger Satisfaction*. Tab. 1 reports the latent variables and the manifest variables used in the measurement model.

Tab. 1. Manifest and Latent Variables

LATENT VARIABLES	MANIFEST VARIABLES
Passenger Satisfaction	*Passenger Satisfaction*
Transportation	*Frequency of Service*
	Regularity of Service
	Security
Information & Security	*Passenger Information* *Staff Behavior* *Personal and Financial Security*
Comfort & Cleaness	*Passenger Comfort*
	Station Cleanness
	Train Cleanness

The spatial dependence between the station is formalized by using the spatial lag variable as defined in formula 4. The definition of the spatial weights matrix **W** is based on distances between the 34 Stations, calculated by using walking Google Map.

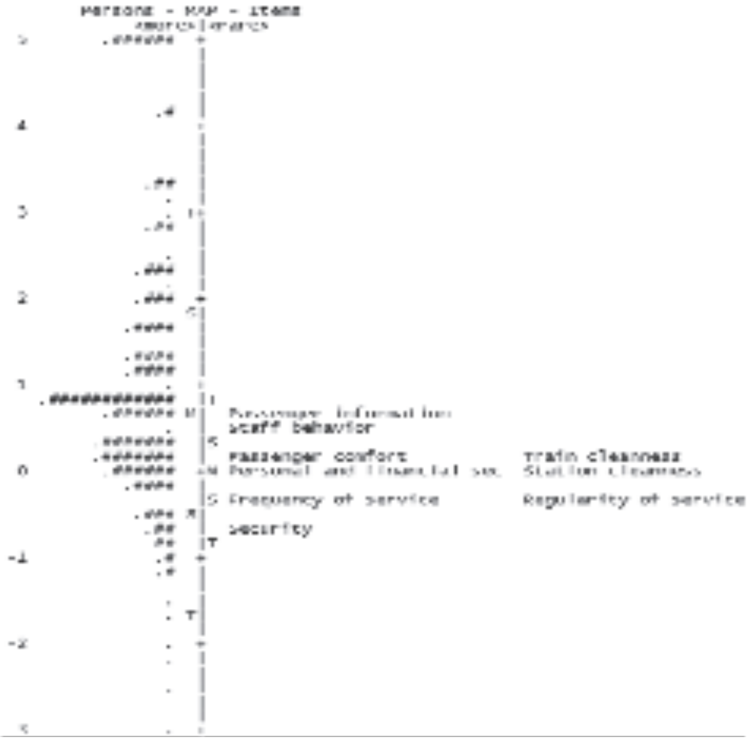
We provide a Passenger satisfaction Model which defines the PS rate in a specific location (Station) h, as a function of the PS rate in a location k (with $h \neq k$). As defined above (*supra* §2.2), the estimation method used is the PLS, performed by using a specific routine developed in Matlab.

3.1 Rating scale model results

The compatibility of the raw data with the Rasch measurement model is verified by several fit statistics. In this case the reliability index observed for items and passengers is 0.99, where the values range between 0 and 1. The estimates for items show how well the replicability of items placement across other passengers measure the same construct index. This result is confirmed by the separation index, whose observed value is equal to 1.

The results for the rating scale analysis of passenger satisfaction are shown in Fig. 1. The vertical line represents the variable passenger satisfaction into log-odds scale. Passengers are aligned to the left and represented by the symbol "#". The more satisfied are on top. Items are aligned to the right. The more the items are on top, the more difficult is to generate satisfaction. It is verified that the distribution of passenger is normal and displayed into higher position than the item distribution. Therefore, passengers have more probability to get satisfaction from metro service.

Fig. 1 - Person-item map for passenger satisfaction



Notes: Each "#" is 27 passengers and aligned to the left of the corresponding log-odds measure of satisfaction. Items are aligned to the right of the corresponding log-odds measure of difficulty to generate satisfaction

More details for item measure are given into Tab. 2. This table lists items in measure order. 'Passenger information' is the attribute of service that has more difficulty to generate satisfaction followed by 'Staff behavior' and 'Train cleanness'. The attributes that have less difficulty to generate satisfaction are 'Security' and 'Regularity of service'. Two types of fit statistics are given for each item. Ideally, the infit and outfit mean-square should be 1.0 for rating scale model, but values included between 0.6 and 1.4 indicate that the deviation from expectation is acceptable (Bond e Fox, 2001). In particular, infit mean-square statistic 1.16 for the item 'Passenger information' is the highest variation between observed data and the Rasch model predicted (16% more variation). 'Train cleanness' and 'Station cleanness' have 18% less variation in the observed response than modeled. Similarly, outfit mean-square for the item 'Passenger information' has the highest variation (20%) and 'Station cleanness' has 17% less variation in the observed data than the model.

Finally, the point-measure correlation is, for each item, a positive value included between 0.58 and 0.68. These values show absence of mis-scoring and normal polarity.

Tab. 2 - Items statistics

Item	Model		Infit	Outfit	Ptmea	Exact	Match
	Measure	S.E.	MnSq	MnSq	Corr.	Obs%	Exp%
Passenger information	.63	.03	1.16	1.20	.63	49.0	50.9
Staff behavior	.45	.03	1.08	1.10	.65	52.4	52.5
Train cleanness	[illegible]	.03	.83	.84	.68	60.2	54.5
Passenger comfort	.19	.03	.89	.93	.64	61.2	53.3
Station cleanness	.08	.03	.82	.83	.67	61.6	55.3
Personal and financial security	0.2	.03	1.11	1.10	.62	54.9	55.6
Frequency of service	-.34	.03	1.05	1.09	.59	56.8	57.7
Regularity of service	-.39	.03	1.07	1.07	.58	56.6	57.8
Security	-.67	.03	.99	.96	.59	61.8	58.8

Notes: Measure is the estimate for the item difficulty to generate satisfaction. S.E. is the standard error of the estimate. Infit MnSq and Outfit MnSq are the infit and outfit mean-square statistic, respectively. Ptmea Corr is the point measure correlation.

The logit measure of each item is obtained for each station by the Differential item function measure (Tab. 3).

Tab. 3 - DIF measure for each item and station

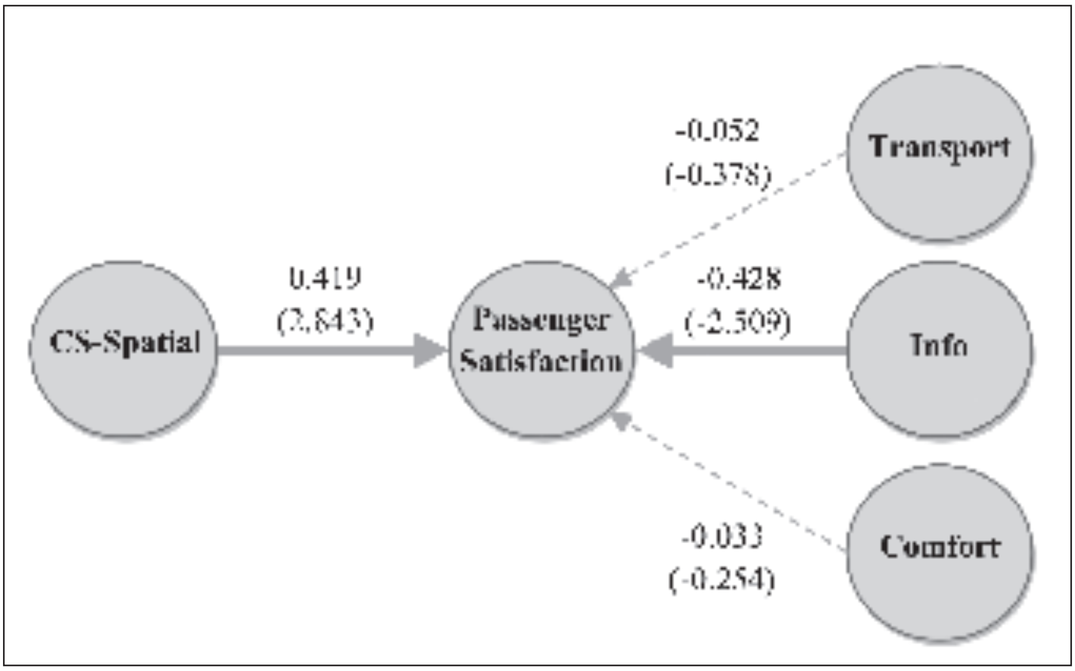
Station	Frequency of service	Regularity of service	Passenger information	Staff behavior	Personal security	Security	Station cleanness	Train cleanness	Passenger comfort
Station1	-0.35	-0.69	0.63	0.57	0.05	-0.62	0.23	0.19	-0.07
Station2	-0.14	-0.02	0.55	0.29	-0.2	-0.82	-0.03	0.21	0.19
Station3	-0.54	-0.34	0.35	0.27	0.01	-0.54	-0.01	0.09	0.53
Station4	-0.68	-0.5	0.43	0.62	0.35	-0.67	-0.15	0.28	0.22
Station5	-0.26	-0.51	0.72	0.74	0.02	-0.59	-0.02	-0.02	-0.13
Station6	-0.31	-0.11	0.5	0.42	0.25	-0.8	-0.13	0.02	0.08
Station7	0.27	0.24	0.54	0.01	0.39	1.21	0.01	0.16	0.3
Station8	0.21	0.14	0.55	0.67	0.21	1.41	0.31	0.31	0.01
Station9	-0.19	0.17	0.38	0.04	0	-1.06	0.5	0.54	0
Station10	0.06	0.06	0.69	0.12	-0.5	-0.92	0.05	-0.02	0.22
Station11	0.23	0.2	0.41	0.23	-0.43	-0.77	-0.17	0.06	0.25
Station12	-0.16	0.08	0.82	0.24	-0.22	-1.17	-0.08	0	0.46
Station13	0.29	0.29	0.27	0.35	0.19	0.28	0	0.12	0.04
Station14	-0.29	0.36	0.42	0.29	0.12	-0.86	-0.06	-0.16	0.26
Station15	-0.15	0.28	0.19	0.36	-0.24	-0.93	-0.15	0.19	0.44
Station16	0.22	-0.16	1.36	-0.02	0.72	-0.58	0.22	-0.16	-0.16
Station17	-0.47	-0.47	0.97	0.14	0.14	-0.47	0.14	-0.15	0.14
Station18	0.1	0.1	0.63	0.1	-0.24	-0.51	-0.19	-0.31	0.41
Station19	-0.13	-1.25	1.15	0.24	0.39	-0.51	0.47	0.54	-0.42
Station20	-0.24	0.82	1.31	0.31	-0.24	-1.63	-0.24	0.82	-1.55
Station21	0.25	-0.37	0.77	-0.57	0.35	-1.73	0.52	0.72	-0.24
Station22	-0.55	-0.35	0.29	0.04	0.39	-0.55	0.22	0.3	-0.66
Station23	-0.41	-0.41	0.65	0.65	-1.41	-1.75	0.65	0.65	0.33
Station24	-0.28	1	1.43	0.18	-0.07	-0.74	-0.01	0.01	1.21
Station25	0.05	0.09	0.19	0.11	0.01	0.25	0.03	0.06	0.01
Station26	-0.26	-0.59	0.28	0.18	-0.07	-0.74	0.05	1.23	0.01
Station27	-0.16	-1.03	1.33	0.85	-0.05	-0.91	0.05	0.32	0.06
Station28	-0.6	-0.6	1.72	1.73	-0.57	-0.66	-0.56	-0.55	-0.56
Station29	-1.29	-1.29	1.16	1.16	-0.15	-0.15	-0.15	-0.15	0.33
Station30	-0.43	-0.97	1.99	1.59	-0.58	-0.97	-0.73	-0.36	-0.43
Station31	1.08	1.3	0.63	0.66	0.11	0.52	0.56	0.56	0.01
Station32	1.07	1.33	0.55	0.85	0.25	0.53	0.01	0.24	0.06
Station33	-1.43	-1.57	0.45	0.6	-0.71	-0.51	0.6	1.04	0.75

3.2 S-SEM results

The estimations of the Passenger Satisfaction Model are represented by the path diagram reported in Fig. 2, which is a graphical representation of a priori specified structures and assumptions. The latent variables are drawn by circles and defined using Greek letters. The unidirectional straight arrows in the path diagram represent the causal influence of one variable on another.

Fig. 2 shows also the estimated path coefficients, where the significant relationships have been highlighted by a bold line and non-significant relationships are shown by broken lines. The number in the brackets is the T-test value. The significance of the variables is calculated via bootstrap re-sampling, considering the 100 samples of dimension 120.

Fig. 2 - The Passenger Satisfaction path model



The S-SEM explains the spatial interaction that characterizes the change in passenger satisfaction among the stations. The spatial autoregressive parameter (ρ) and the (β) structural coefficient estimated are significant, while parameter estimates of the other latent variables are not significant.

The spatial lag result suggests that the PS rate in a location *h* has a significant positive dependence from the PS level in another location *k* (0.419). This means the satisfaction in a specific station steps up if the satisfaction in the neighboring areas increases.

The latent variables are measured as the complexity to generate satisfaction. Therefore a negative value of the path coefficient increases the satisfaction, while a positive value decreases the satisfaction. The only latent variable that is significant, with a T-test value greater than 2, is the *Info*, with a path coefficient equal to -0.428, thus implying a good impact in increasing the satisfaction.

For improving the interpretation of the results and for giving a valid support to decision makers, Tab. 4 reports the estimated values of the Latent Variables, obtained as the weighted average value based on the tau (τ) coefficients of the manifest variables.

Tab. 4 - Estimated Value of the Latent Variables

Latent Variables	Estimated Value
Transportation	-0.134
Info	0.276
Comfort	-0.010

The estimated values of the LVs *Transportation* (-0.134) and *Comfort* (-0.010) show that these variables have a low value of difficulty to generate satisfaction, that is the passengers give a good evaluation of these aspects. *Info* (0.276) is evaluated with a high level of difficulty, so the passengers are not satisfied with this aspect.

By combining the results of the path coefficients and the level of PS it is possible to define an intervention matrix by the categorization into two groups of difficulty level as reported in Tab. 5. The LV of the first group has a relative low level of difficulty (good evaluation) and the variables in the second group have a high level of difficulty (bad evaluation).

Tab. 5 - Interventions Matrix

		Difficulty	
		Low	High
Importance	Low (or non significant)	*Transportation* *Comfort*	
	High		*Info*

Tab. 5 can be interpreted as the aspects that can be improved: *Info* is the most important variable in this case study.

Tab. 6 can help in the analysis of which aspects of the *Info* Latent Variable have to be improved. It is possible to read that *PassInfo* (0.8722) and *Staff-B* (0.1173) are the items with major difficulty in creating satisfaction, where instead *PersFin* is the only with a low level of difficulty (-0.2593).

Tab. 6 - Lambda coefficients of the Manifest Variables

Latent Variables	Manifest Variables	Weights	(s.e.)	T-Statistic
Transportation	***FreqServ***	0.3978	0.1771	2.2464
	RegServ	0.6366	0.1507	4.2233
	Security	-0.0429	0.2534	-0.1693
Info	***PassInfo***	0.8722	0.1231	7.0874
	Staff-B	0.1173	0.1593	0.7362
	PersFin	-0.2593	0.157	-1.6518
Comfort	***P-Comf***	-0.3177	0.3168	-1.0029
	St-Clean	0.8226	0.2914	2.8234
	T-Clean	0.2233	0.2709	0.8244

References

Andrich D. (1978), *A rating formulation for ordered response categories*, Psychometrika, 43, 561-574.

Anselin L. (2001), *Spatial Econometrics. In A companion to theoretical econometrics*, ed. B.H.

Bernardini Papalia R. (2006), *Modeling mixed spatial processes and spatio-temporal dynamics in Information theoretic frameworks*, COMPSTAT, in Rizzi A., Vichi M. (Eds), Physica Verlag Heidelberg, New York, 1483-1491.

Bernardini Papalia R., Ciavolino E. (2008), *GME estimation of spatial structural equations models*, in: MTISD (2008), *Methods, Models and Information Technologies for Decision Support Systems*, Lecce, 18 - 20 Settembre 2008, 228-231.

Bond T.G., Fox C.M. (2001). *Applying the Rasch model: Fundamental measurement in the human sciences*, Erlbaum, London.

Ciavolino E., Al-Nasser A.D. (2009), *Comparing Generalized Maximum Entropy and Partial Least Squares methods for Structural Equation Models*, Journal of Nonparametric Statistics, 21(8), 1017-1036.

Gallo M. (2007), *The scaling problems in service quality evaluation*, Metodološki Zvezki, 2, 165-176.

Gallo M. (2009), *Measuring the passenger satisfaction: A strategy based on Rasch Analysis and Analysis of Means (ANOM)*. Submitted.

Linacre J.M., Wright B.D. (2000), *A user's guide to WINSTEPS: Rasch model computer program,* MESA Press, Chicago.

Wright B.D., Masters G.N. (1982), *Rating scale analysis*, MESA Press, Chicago.

Wold H. (1966), *Estimation of principal components and related models by iterative least squares*, in Multivariate Analysis, ed. P.R. Krishnajah, Academic Press, New York, 391–420.

Wold H. (1973), *Nonlinear Iterative Partial Least Squares (NIPALS) Modelling - Some Current Developments*, in Multivariate Analysis, 3, ed. P.R. Krishnajah, Academic Press, New York, 383–407.

Wold H. (1975), *Path Models with Latent Variables. The NIPALS Approach,* in Quantitative Sociology, ed. H.M. Blalock, New York: Seminar Press, 307–357.

Wold H. (1982), *Soft Modelling: The basic design and some extensions*, in

Systems Under Indirect Observations, part 2, eds. K.G. Jöreskog and H. Wold, North-Holland, Amsterdam, 1–54.

Wold H. (1985), *Partial Least Squares*, in Encyclopaedia of Statistical Sciences, 6, eds. S. Kotz and N.L. Johnson, John Wiley & Sons, New York, 581–591.