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Generalized cross entropy method for analysing the SERVQUAL model

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The aim of this paper is to define a new approach for the analysis of data collected by means of SERVQUAL questionnaires which is based on the generalized cross entropy (GCE) approach. In this respect, we firstly give a short review about the important role that SERVQUAL plays in the analysis of service quality as well as in the assessment of the competitiveness of public and private organizations. Secondly, we provide a formal definition of GCE approach together with a brief discussion about its features and usefulness. Finally, we show the application of GCE for a SERVQUAL model, based on a patients' satisfaction case study and we discuss the results obtained by using the proposed GCE-SERVQUAL methodology.

Keywords: generalized cross entropy; SERVQUAL; gap analysis; patient satisfaction

1. Introduction

Service quality (SQ) plays a central role in the analysis of competitiveness of service industries (e.g. public school and universities, hospitals, and tourism agencies) and private economic companies (e.g. restaurant, outlet stores). In the analysis of SQ, several sources of *quality* are usually considered in the economic and management literature [20,34]. For instance, *internal quality* refers to goods or services which are conformed to some standard requirements that are declared by an organization agency or by the same organizations which offer such goods or services. On the contrary, the *external quality* refers to goods or services which are conformed to some standard requirements defined by customers. In this particular case, the organization has also to determine the customer's expectations as well as the correct way to satisfy such customers' needs. For this reason, measuring the external SQ can be considered an important step for promoting the customers' satisfaction and the customers' loyalty. To this end, for instance, several models and methodologies may be employed (e.g. the Total SQ model, Expectations-Disconfirmation model and the SERVQUAL model) [26,30,31,40,43]. In general, from a methodological viewpoint, SQ can be considered a three-dimensional construct with three

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levels: *physical* (the conditions in which the organization works), *corporate* (image of the organization) and *interactive* (relational dimension in which the organization meets the customers) [32]. By and large, two main perspectives can be considered in order to analyse such latent dimensions, namely analysing the *process* underlying the observed quality or analysing the *outcome* of such process.

A first special attempt in providing a flexible and simple methodology to measure SQ was performed by Parasuraman [38]. He proposed the well-known *SERVQUAL methodology* with the attempt to integrate the information obtained by analysing process and outcome. SERVQUAL is a widely used methodology (e.g. in economics, sociology, management sciences, marketing researchers and organizational psychology) which allows to measure SQ by taking into account the customers' expectations and perceptions about the services that are provided by the organization. Several statistical methods and techniques may be used to analyse the SERVQUAL-based SQ dimensions. In particular, the so-called *gap analysis* can be employed in order to show some relevant features which are related to the natural gap existing between customers' expectations and customers' perceptions [7,26]. Moreover, gap analysis (and the corresponding *gap scores*) may reveal some interesting features concerning the eventual difference between what is expected and what is perceived by the customers. To this end, several methods have extensively been used. For instance, gap scores may be simply evaluated by adopting: statistical test for mean differences (t-test) [9,25], factorial analysis [7], multi-step procedures where gap scores are aggregated, weighted by suitable loadings (e.g. those provided by factorial analysis) and then tested in their differences [6], ANOVA designs [35], step-wise regression analysis in which aggregated and weighted gap scores are used as predictors [7], co-inertia analysis [1], structural equation models [16], correspondence analysis [3], etc. In general, once the gap scores are obtained the choice of statistical analysis depends on the specific purposes and needs of the researchers [40].

In line with the previous studies, in this article we propose a novel methodology (called *GCE-SERVQUAL*) for assessing the gap scores between customers' expectations and customers' perceptions, which is based on the generalized cross entropy (GCE) approach [23]. In sum, the GCE-SERVQUAL allows to evaluate the gap scores by defining a unified model which takes into account the magnitude of the customers' expectations on the customers'perceptions. Unlike the previous method, the proposed approach allows to consider the customers' expectations as *prior information* as well as to consider more realistically the magnitude of the final perceptions on the SQ measurement.

The remainder of this article is organized as follows. In the second section, we briefly recall the rationale underlying the SERVQUAL methodology and the gap scores analysis as proposed by Parasuraman *et al*. [37,38]. In the third section, we describe the main features of the GCE approach. In order to show the characteristics of the proposed approach, in the fourth section, we describe a real case study in which we analyse the Patient Satisfaction from a GCE-SERVQUAL perspective. Finally, in the fifth section, we provide final comments as well as future suggestions for further developments of our proposal.

2. SERVQUAL model

In a seminal paper, Parasuraman *et al*. [37] proposed that SQ is a function of the differences between customers' expectations and customers' perceptions. They developed a peculiar theoretical framework for the measurement of SQ, also known as *the gap model*, where SQ is evaluated by five main gaps (difference between customers' expectations and management's perceptions, difference between management's expectation and customers' perceptions, difference between SQ specifications and service actually delivered, difference between service delivery and communications about service delivery, difference between customers' expectation and perceived service). According to this framework, perceived SQ, for the ith statistical units, can be defined as follows:

$$\mathrm{SQ}_i = \sum_{j=1}^{m} x_{ij}^{\mathrm{per}} - x_{ij}^{\mathrm{exp}},$$

where x_{ij}^{per} is the perception measure of the ith statistical units on the jth attribute of the SQ dimensions; x_{ij}^{exp} is the expected measure of the ith statistical units on the jth attribute of the SQ dimensions. More qualitatively, we have the following scenario:

(1) when perceived service is less than expected service ($x_{ij}^{\mathrm{per}} < x_{ij}^{\mathrm{exp}}$), the perceived quality of the service tends to be unacceptable (*dissatisfaction*);
(2) when perceived service is greater than expected service ($x_{ij}^{\mathrm{per}} > x_{ij}^{\mathrm{exp}}$), the perceived quality of the service tends to be idealized (*ideal quality*);
(3) when perceived service is equal to expected service ($x_{ij}^{\mathrm{per}} = x_{ij}^{\mathrm{exp}}$), the perceived quality of the service tends to be acceptable (*satisfaction*).

In other terms, negative gap scores highlight that the consumer was amazed by the service (*surprise effect*) whereas positive gap scores indicate that expectations are not just being met but exceeded. Generally, when expectations overtake perceptions, small negative scores can suggest a good serviceİ [19,24].

The SERVQUAL questionnaire proposed later by Parasuraman *et al*. [38] comprises 22 items across 5 dimensions (namely *tangibles, reliability, responsiveness, assurance and empathy*) where, in his rationale, each item is measured twice: once for measuring expectations and once for measuring perceptions. This methodology has been widely used in several research context, such as for instance health-care applications [5,19,24], diagnosis and medical evidences [33], experimental economy [8] and SQ assessment [7,44]. Whilst several studies have shown the reliability and the validity of this methodology [2,4,16], some criticisms have been raised against SERVQUAL over the years [30]. However, despite this, SERVQUAL can still be considered a standard, simple and reliable tool for measuring SQ in various organizational contexts.

3. GCE and SERVQUAL methodology

In this section we describe the proposed GCE-SERVQUAL model together with its main features. However, before introducing our proposal, we briefly explain the GCE rationale within the more general and simple case of linear models.

3.1 *GCE approach*

GCE approach was firstly proposed by Golan *et al*. [23] as a generalization of the well-known Maximum Entropy principle described by Jaynes [27,28]. Jaynes's idea is mainly based on the principles of Shannon's Information Theory and Shannon's entropy [15,41]. In qualitative terms, entropy is a measure of the average information carried out by a probabilistic source of data. In many statistical applications, entropy can be used as information recovering device (e.g. from ill-posed problems: short and fat matrices, multicollinearity) as well as method of estimation [12,14,36]. In this line, Golan's idea [21–23] is to apply a slightly modified maximum entropy-based method, called GCE, in order to estimate the parameters of some statistical models, such as for instance regression models, simultaneously equation models and dynamic models. More formally, let us consider the following linear model for the ith unit with n observations and m

variables (for the sake of simplicity, we omit the intercept):

$$y_i = \sum_j^m x_{ij}\beta_j + \epsilon_i.$$

the idea of GCE is the re-parametrization of each model parameter (β_j, ϵ_i) as the expected value of a discrete random variable as follows:

$$\beta_j = \sum_k^K z_{jk}^\beta p_{jk}^\beta \ \ \forall j, \quad \epsilon_i = \sum_h^H z_{ih}^\epsilon p_{ih}^\epsilon \ \ \forall i,$$

where z_{jk}^β is the generic element of the support variable $\boldsymbol{z}_j^\beta$ which is, in turn, a $K \times 1$ symmetric vector around zero (with $3 \leq K \leq 7$), p_{jk}^β is the generic element of the probability vector $\boldsymbol{p}_j^\beta$ associated to $\boldsymbol{z}_j^\beta$; z_{ih}^ϵ is the generic element of the support variable $\boldsymbol{z}_i^\epsilon$ which is still a symmetric vector around zero, whereas, like the previous case, p_{ih}^ϵ is the generic element of the probability vector $\boldsymbol{p}_i^\epsilon$ related to $\boldsymbol{z}_i^\epsilon$ (note that also in this case $3 \leq H \leq 7$).

Bearing this in mind, the GCE linear model for the ith unit takes the following form:

$$y_i = \sum_j^m x_{ij} \sum_k^K z_{jk}^\beta p_{jk}^\beta + \sum_h^H z_{ih}^\epsilon p_{ih}^\epsilon.$$

Note that, the vectors $\boldsymbol{z}_j^\beta$ and $\boldsymbol{z}_i^\epsilon$ play an important role in the estimation procedure. A relevant issue concerns the choice of their supports. In particular, they may be set up by using some objective prior information, fixed ad hoc (as we will see in Section 4) and/or by using the *three-sigma-rule* [13,39]). It is straightforward to note that, in this context, the probability distributions $\boldsymbol{q}_j^\beta$ and $\boldsymbol{q}_i^\epsilon$ codify the prior information associated to the model parameters.

The unknown parameters of the GCE linear model are estimated recovering the corresponding probability distributions, $\boldsymbol{p}_j^\beta$ $\forall j = 1, \ldots, m$ and $\boldsymbol{p}_i^\epsilon$ $\forall i = 1, \ldots, n$ by solving the following minimization problem:

$$\text{GCE-problem} \begin{cases} \text{Minimize:} & \displaystyle\sum_j \sum_k p_{jk}^\beta \log \frac{p_{jk}^\beta}{q_{jk}^\beta} + \sum_i \sum_h p_{ih}^\epsilon \log \frac{p_{ih}^\epsilon}{q_{ih}^\epsilon} \\ \text{Subject to:} & \displaystyle\sum_k p_{jk}^\beta = 1 \ \ \forall j, \\ & \displaystyle\sum_h p_{ih}^\epsilon = 1 \ \ \forall i, \\ & \displaystyle\sum_j x_{ij} \sum_k z_{jk}^\beta p_{jk}^\beta + \sum_h z_{ih}^\epsilon \, p_{ih}^\epsilon = y_i \ \ \forall i, \end{cases}$$

where the first two equations are called *normalization constraints* whereas the last equation is the so-called *consistency constraint*. The problem can be solved, for instance, using the Lagrangian method, as follows:

$$\mathcal{L} = \left[\sum_j \sum_k p_{jk}^\beta \log \left(\frac{p_{jk}^\beta}{q_{jk}^\beta} \right) + \sum_i \sum_h p_{ih}^\epsilon \log \left(\frac{p_{ih}^\epsilon}{q_{ih}^\epsilon} \right) \right]$$

$$+\sum_i^n \lambda_i' \left[y_i - \sum_j^m x_{ij} \left(\sum_k^K z_{jk}^{\beta} p_{jk}^{\beta} \right) - \left(\sum_h^H z_{ih}^{\epsilon} p_{ih}^{\epsilon} \right) \right]$$
$$+\sum_j^m \theta_j' \left(1 - \sum_k^K p_{jk}^{\beta} \right) + \sum_i^n \theta_i'' \left(1 - \sum_h^H p_{ih}^{\epsilon} \right).$$

By equating to zero the gradient of the above function $\nabla(\mathcal{L}) = \mathbf{0}$ (first-order condition), we obtain the following parametrized solutions:

$$\hat{p}_{jk}^{\beta} = \frac{q_{jk}^{\beta} \exp(\hat{\theta}_j' x_{i,j})}{\Omega_j(\hat{\theta}_j')} \quad \hat{p}_{ih}^{\epsilon} = \frac{q_{ih}^{\epsilon} \exp(\hat{\theta}_i'')}{\Psi_i(\hat{\theta}_i'')},$$

where $\Omega_j(\hat{\theta}_j') = \sum_k q_{jk}^{\beta} \exp(\hat{\theta}_j' x_{i,j})$ and $\Psi_i(\hat{\theta}_i'') = \sum_h q_{ih}^{\epsilon} \exp(\hat{\theta}_i'')$ represent the normalization factors for the probability distributions associated with the model parameters, whereas $\hat{\theta}_j'$ and $\hat{\theta}_i''$ represent the Lagrangian multipliers which are numerically found [23]. Note that, by allowing stochastic moments and using the relative entropy as the objective, all the errors are pushed toward zero but not force them to be exactly zero. In this way, the samples moments are allowed (but not forced) to be different from the underlying population moments.

3.2 *GCE-SERVQUAL approach*

In this section we describe the proposed GCE-SERVQUAL methodology. From an information-theoretic viewpoint, the main idea is to evaluate the impact of perception measures on the global quality by taking into account the information provided by the expectation measures. Unlike other methods, which estimate the impact of perceptions given the expectations by using their differences (empirical gap scores), in our proposal we study how the strength and direction of the perceptions can be augmented or diminished according to the expectations.

3.2.1 *Model*

Let $\boldsymbol{y}$ be the $n \times 1$ vector containing the values of global quality, $\boldsymbol{X}^{\text{per}}$ the $n \times m$ matrix of perceptions and $\boldsymbol{X}^{\text{exp}}$ the $n \times m$ matrix of expectations (in the standard SERVQUAL representation, $m = 5$). The GCE-SERVQUAL model can be expressed as

$$y_i = \sum_j^m x_{ij}^{\text{per}} \cdot \beta_j^{ce} + \epsilon_i^{ce} \quad \text{with: } \beta_j^{ce} = \sum_k^K z_{kj}^{\beta^{ce}} p_{kj}^{\beta^{ce}} \quad \text{and} \quad \epsilon_i^{ce} = \sum_h^H z_{hi}^{\epsilon^{ce}} p^{\epsilon^{ce}} \tag{1}$$

where y_i is the value of the global quality measured for the ith statistical units, x_{ij}^{per} is the perception value for the ith statistical units on the jth dimension of the SERVQUAL, β_j^{ce} expresses the magnitude of the corresponding dimension on the global quality whereas ϵ_i^{ce} is the residual term. Note that, $\boldsymbol{\beta}^{ce}$ provides all the information about the role that the perception measures have on the global quality $\boldsymbol{y}$ and, in our model, it is represented by the convex combination $\sum_k^K z_{kj}^{\beta^{ce}} p_{kj}^{\beta^{ce}}$ $(j = 1 \dots m)$. As described in the previous section, in the GCE approach the numerical representation for $\boldsymbol{\beta}^{ce}$ can be obtained by Lagrange method on the following entropy measure:

$$\sum_j \sum_k p_{kj}^{\beta^{ce}} \log\left(\frac{p_{kj}^{\beta^{ce}}}{q_{kj}^{\beta^{\exp}}}\right) + \sum_i \sum_h p_{hi}^{\epsilon^{ce}} \log\left(\frac{p_{hi}^{\epsilon^{ce}}}{q_{hi}^{\epsilon^{\exp}}}\right) \tag{2}$$

which yields, in turn, to the following solutions:

$$\hat{p}_{kj}^{\beta^{ce}} = \frac{q_{kj}^{\beta^{\exp}} \exp(\hat{\theta}_j' x_{i,j})}{\Omega_j(\hat{\theta}_j')} \quad \hat{p}_{hi}^{\epsilon^{ce}} = \frac{q_{hi}^{\epsilon^{\exp}} \exp(\hat{\theta}_i'')}{\Psi_i(\hat{\theta}_i'')} \tag{3}$$

Note that, Equations (3) contain the terms $q_{kj}^{\beta^{\exp}}$ and $q_{hi}^{\epsilon^{\exp}}$ which constitute the prior information about the expectations. These terms act by augmenting or diminishing the magnitude of $\hat{p}_{kj}^{\beta^{ce}}$ and $\hat{p}_{hi}^{\epsilon^{ce}}$ according to the information available. In this way, we are able to modulate the strength and direction of the perceptions coefficients by taking into account the external information provided by the expectation measures.

3.2.2 *Estimation procedure*

GCE-SERVQUAL approach implements a *two-step procedure* in order to obtain $\hat{p}_{kj}^{\beta^{ce}}$ and $\hat{p}_{hi}^{\epsilon^{ce}}$. In particular, the proposed approach firstly estimates the priors $q_{kj}^{\beta^{\exp}}$ and $q_{hi}^{\epsilon^{\exp}}$ and then it obtains the targets $\hat{p}_{kj}^{\beta^{ce}}$ and $\hat{p}_{hi}^{\epsilon^{ce}}$ as follows:

$$\text{I step}\begin{cases} \text{Minimize:} & \displaystyle\sum_j \sum_k q_{kj}^{\beta^{\exp}} \log\left(\frac{q_{kj}^{\beta^{\exp}}}{w_{kj}^{\beta}}\right) + \sum_i \sum_h q_{hi}^{\epsilon^{\exp}} \log\left(\frac{q_{hi}^{\epsilon^{\exp}}}{w_{hi}^{\epsilon}}\right) \\ \text{Subject to:} & \displaystyle\sum_k q_{kj}^{\beta^{\exp}} = 1, \\ & \displaystyle\sum_h q_{hi}^{\epsilon^{\exp}} = 1, \\ & \displaystyle\sum_j x_{ij}^{\exp} \sum_k z_{kj}^{\beta^{\exp}} q_{kj}^{\beta^{\exp}} + \sum_h z_{hi}^{\epsilon^{\exp}} p_{hi}^{\epsilon^{\exp}} = y_i \ \ \forall i, \end{cases} \tag{4}$$

$$\text{II step}\begin{cases} \text{Minimize:} & \displaystyle\sum_j \sum_k p_{kj}^{\beta^{ce}} \log\left(\frac{p_{kj}^{\beta^{ce}}}{\hat{q}_{kj}^{\beta^{\exp}}}\right) + \sum_i \sum_h p_{hi}^{\epsilon^{ce}} \log\left(\frac{p_{hi}^{\epsilon^{ce}}}{\hat{q}_{hi}^{\epsilon^{\exp}}}\right) \\ \text{Subject to:} & \displaystyle\sum_k p_{kj}^{\beta^{ce}} = 1, \\ & \displaystyle\sum_h p_{hi}^{\epsilon^{ce}} = 1, \\ & \displaystyle\sum_j x_{ij}^{\text{per}} \sum_k z_{kj}^{\beta^{ce}} p_{kj}^{\beta^{ce}} + \sum_h z_{hi}^{\epsilon^{ce}} p_{hi}^{\epsilon^{ce}} = y_i \ \ \forall i, \end{cases} \tag{5}$$

where w_{kj}^{β} and w_{hi}^{ϵ} in Equation (4) are $K \times 1$ and $H \times 1$ probability vectors following a discrete uniform distribution, respectively. The estimation procedure on both steps can be attained as described earlier, yielding to the same solutions reported in Equation (3).

3.2.3 *Model evaluation*

In this subsection we illustrate some useful procedures to assess the performance and reliability of the GCE-SERVQUAL model.

Goodness of fit. In order to evaluate the performance of the GCE-SERVQUAL model, we consider the following GCE-based normalized index [22,23]:

$$R^2_{pseudo} = 1 - \frac{\sum_j^m \sum_k^K \hat{p}_{jk}^{\beta^{ce}} \log(\hat{p}_{jk}^{\beta^{ce}})}{m \log(K)} \quad (6)$$

which captures the *reduction of uncertainty* that is produced by the consistency constraints defined in the GCE-optimization problem. Its interpretation is similar to Soofi's pseudo-R^2 [42]. In particular, when R^2_{pseudo} tends to 0 the portion of uncertainty explained by the model is very low, whereas, on the contrary, when R^2_{pseudo} tends to 1 the reduction of uncertainty is considered significant.

Reliability. To assess the accuracy of the GCE-SERVQUAL solutions, we used a non-parametric bootstrap procedure for GCE models [12,14,36]. In particular, in the non-parametric bootstrap Q samples (with $Q \geq 1000$) of size (n) were row-wise randomly drawn (with replacement) from the original matrices $\boldsymbol{X}^{\text{per}}$, $\boldsymbol{X}^{\text{exp}}$ and vector $\boldsymbol{y}$. For each qth sample, the GCE-SERVQUAL parameters $\boldsymbol{\beta}^{ce}$, $\boldsymbol{\epsilon}^{ce}$, $\boldsymbol{\beta}^{\text{exp}}$, $\boldsymbol{\epsilon}^{\text{exp}}$ were derived by applying the proposed estimation procedure on the sample matrices $\mathbf{X}_{\mathbf{q}}^{\text{per}}$, $\mathbf{X}_{\mathbf{q}}^{\text{exp}}$ and vector $\boldsymbol{y}_q$. These steps were then repeated for Q times. Finally, the ensuing sample parameter distributions were then used for computing the standard errors or confidence intervals (95% CIs) for every estimated parameter in the model. In general, the lower the standard errors, the greater the accuracy of the model.

4. Patient satisfaction case study

In this section we describe a real application concerning Patient Satisfaction to illustrate the main features of the GCE-SERVQUAL approach. All the algorithms developed for these applications are available upon request to the authors.

4.1 *Data and procedure*

Data were collected by using a SERVQUAL questionnaire with 5-point Likert scale for the evaluation of the patients satisfaction (see Table 1). In particular, a questionnaire with 19 items were administered to a sample of subjects from some Italian hospitals located in Campania region (South of Italy) from January to June 2002. The sample was composed of all of the patients available in the structures for the survey during the time period (non-probabilistic sample). The questionnaires were administered in the Departments of Surgical Sciences, Oncology, Auxo-Endocrinology, ENT, Ophthalmology, Dentistry and General Surgery. Valid questionnaires returned at the end of the administration period were 511 (rate of nonresponse or partial response was about 9%). Following the standard SERVQUAL methodology, questionnaires were administered twice to the patients (in case of children, they were administered to the parents): at the

Table 1. Descriptive gap analysis of the five SERVQUAL dimensions.

	Expectations	Perceptions	Gap scores
Tangibility	1.440	0.775	0.665
Reliability	1.379	0.952	0.426
Responsiveness	1.371	1.171	0.200
Assurance	1.556	1.157	0.399
Empathy	0.676	0.254	0.422

admission to the hospital (for measuring the expectations) and at the dismission from the hospital (for measuring the perceptions). A detailed discussion and presentation of the data can be found in [17,18].

4.2 *Variables*

Once data were collected, they were firstly converted from ordinal to cardinal measures using a well-known and widely adopted procedure [14]. This would improve the mathematical representation of the collected data. Finally, the converted data were standardized. Next, variables for the analyses were computed as follows:

(1) an outcome variable called *global satisfaction* (in our model representation $\boldsymbol{y}$) obtained as the average of the corresponding SERVQUAL items (namely, *Judgement about the hospital*, *Judgement about the hospital personnel*, *Judgement about the hospital nurses* and *Judgement about the hospital machinery*);
(2) five SERVQUAL variables (namely, *tangibility*, *reliability*, *responsiveness*, *assurance*, *empathy*) obtained as the average of the corresponding group of SERVQUAL items (see Table 1). This procedure was repeated twice, for the expectation and perception data, obtaining so the matrices of expectations and perceptions (in our model representation $\boldsymbol{X}^{\text{exp}}$ and $\boldsymbol{X}^{\text{per}}$, respectively).

4.3 *Data analysis*

4.3.1 *Descriptive gap analysis*

In order to compare and evaluate from a descriptive viewpoint the results provided by the expectation and perception scenarios, we report as follows. Table 1 shows the mean values for the five SERVQUAL variables together with the corresponding gap scores. We can observe how expectations always exceed perceptions along the five SERVQUAL dimensions. In particular, we can note that the largest gap score is obtained for the tangibility aspects of the health-care service whereas, on the contrary, the smallest gap score is obtained for the Responsiveness dimension. Figure 4.3.1 gives the same information from a graphical perspective.

4.3.2 *GCE gap analysis*

In what follows we apply the proposed method to the Patient Satisfaction variables. In order to facilitate discussions of similarity and differences between the GCE-SERVQUAL and the standard regression-based gap analyses [30], we tested four models in which we analyse: (i) the relation between expectations and global satisfaction (model 1), (ii) perceptions and global satisfaction (model 2), (iii) difference expectations/perceptions (gap scores) and global satisfaction (model 3) and (iv) perceptions given the expectations and global satisfaction (model 4).

Model 1. This linear model evaluates the expectations on the global satisfaction. By considering the first descriptive results in Table 1, we expect that the higher the expectations the lower the global satisfaction. Although different scenarios may arise from the relation between expectations and global satisfaction (e.g. low expectation/low satisfaction, low expectation/high satisfaction and high expectation/high satisfaction), we prefer to consider the simple but reasonable higher expectation/lower satisfaction relation, as also suggested by the descriptive gap analysis results (Table 1). As a formal level, this model is

$$\boldsymbol{y} = \boldsymbol{X}^{\text{exp}}\boldsymbol{\beta}^{\text{exp}} + \boldsymbol{\epsilon},$$

where $\boldsymbol{X}^{\text{exp}}$ is the matrix containing the expectations measures, $\boldsymbol{\beta}^{\text{exp}}$ is the corresponding vector of regression parameters and $\boldsymbol{y}$ is the vector that contains the global satisfaction measures. Note that, the model can be easily estimated by using the I-step of the GCE-SERVQUAL approach (see Equation (4)) through the GCE re-parametrization of the model parameters.

Model 2. This model evaluates the relation between perceptions and global satisfaction and gives us information about what aspects of the services should be improved in order to obtain a good global satisfaction. More formally, this model is

$$\boldsymbol{y} = \boldsymbol{X}^{\text{per}}\boldsymbol{\beta}^{\text{per}} + \boldsymbol{\epsilon}$$

where $\boldsymbol{X}^{\text{per}}$ is the matrix that contains the perception measures, $\boldsymbol{\beta}^{\text{per}}$ is the corresponding vector of regression parameters and $\boldsymbol{y}$ is still the vector containing the global satisfaction measures.

Model 3. This third model evaluates the impact of the difference between expectations and perceptions on the global satisfaction. In particular, it provides information about the *shock* which is generated by the distance between what is expected and what actually is perceived by the patients. The model is

$$\boldsymbol{y} = (\boldsymbol{X}^{\text{per}} - \boldsymbol{X}^{\text{exp}})\boldsymbol{\beta}^{\text{diff}} + \boldsymbol{\epsilon},$$

where $\boldsymbol{X}^{\text{per}} - \boldsymbol{X}^{\text{exp}}$ is the matrix containing the difference terms (gap scores), $\boldsymbol{\beta}^{\text{diff}}$ is the corresponding vector of regression parameters and $\boldsymbol{y}$ is defined as above.

Model 4. This final model evaluates the impact of the perceptions given the expectations on the global satisfaction. It corresponds to the GCE-SERVQUAL model defined in Equation (1) and, therefore, is computed by using the two-step procedure described in Section 3.2.2. Without loss of generality, we codify this model as

$$\boldsymbol{y} = \boldsymbol{X}^{\text{per}}\boldsymbol{\beta}^{\text{ce}} + \boldsymbol{\epsilon},$$

where the terms of the equation are defined as in the previous cases. Obviously, in this case, the estimation of $\boldsymbol{\beta}^{ce}$ requires the information of $\boldsymbol{\beta}^{\text{exp}}$ which is specifically added in the model formulation, as described in Equations (4) and (5).

It is important to remark that, the first three cases (Models 1–3) are simple linear models which can be estimated by applying the I-step of the GCE-SERVQUAL approach. Note also that, in the GCE estimation of the Models 1–3, $\boldsymbol{w}^{\beta}$ and $\boldsymbol{w}^{\epsilon}$ must follow uniform distributions which, in this particular case, are defined as $w_j^{\beta} = (\frac{1}{5}, \frac{1}{5}, \frac{1}{5}, \frac{1}{5}, \frac{1}{5})$, $j = 1 \ldots m$, $K = 5$, and $w_i^{\epsilon} = (\frac{1}{5}, \frac{1}{5}, \frac{1}{5}, \frac{1}{5}, \frac{1}{5})$, $i = 1 \ldots n$, $H = 5$. In these cases, GCE is equivalent to generalized maximum entropy approach [23]. On the contrary, the last case (Model 4) is the proposed GCE-SERVQUAL model which takes into account the expectation measures in the estimation procedure. In order to apply the GCE method of estimation, in general we firstly have to define the support vectors $\boldsymbol{z}^{\beta^{(.)}}$ and $\boldsymbol{z}^{\epsilon}$ that can be fixed to be as larger as possible for the sake of generality [11,13,36]. In this case, we set $z_j^{\beta^{(.)}} = (-100, -50, 0, 50, 100)$, $j = 1 \ldots m$, $K = 5$, and $z_i^{\epsilon} = (-3\hat{\sigma}_{\mu}, -1.5\hat{\sigma}_{\mu}, 0, 1.5\hat{\sigma}_{\mu}, 3\hat{\sigma}_{\mu})$, $i = 1 \ldots n$, $H = 5$.

4.4 *Results and discussion*

Table 2 shows the estimated regression coefficients of the four regression models whereas Figures 1–3 show the estimated probability distributions $\hat{p}_j^{\beta^{(.)}}$ for each regression coefficient.

In general, all the estimated models showed very good fit indices (see Table 3). The results for Model 1 (*model of expectations*) indicates that some of the SERVQUAL variables for expectations (Tangibility, Responsiveness, Assurance, Empathy) inversely relate to the global satisfaction whereas, on the contrary, only one of them (Reliability) is directly associated to the

Table 2. Regression coefficients for the four models analysed.

	expectations	perceptions	cross-entropy	differences
β_1	−0.387	0.272	0.336	−0.189
β_2	0.064	0.105	0.039	0.035
β_3	−0.365	0.301	0.374	−0.144
β_4	−0.065	0.123	−0.011	−0.125
β_5	−0.058	−0.027	−0.040	−0.059

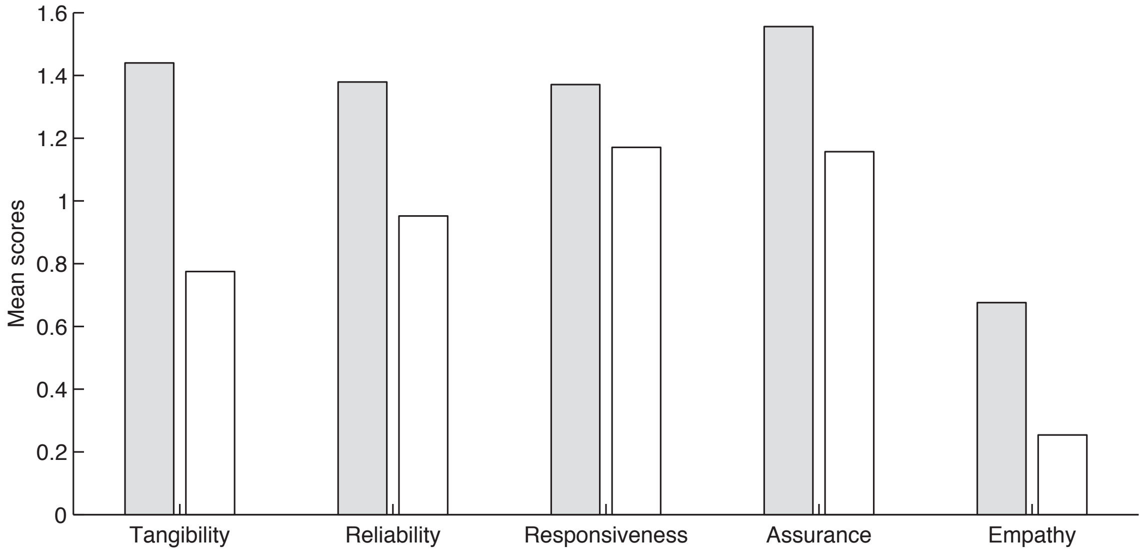

Figure 1. Bar plot for the gap scores (expectations are represented in grey whereas perceptions in white).

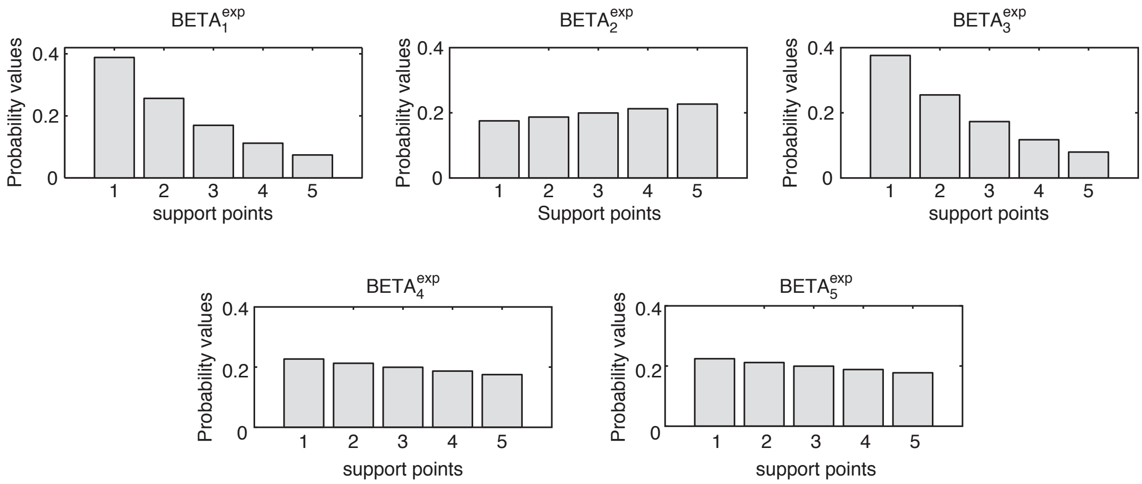

Figure 2. Model 1: probability distributions of the regression coefficients.

global satisfaction (although its regression coefficient takes values close to zero). In particular, expected tangibility and responsiveness had a strong negative relation with the global satisfaction ($\beta_1^{\text{exp}} = -0.38$ and $\beta_3^{\text{exp}} = -0.36$) whereas the other expected variables showed both positive and negative weak relations with the dependent variable ($\beta_2^{\text{exp}} = 0.06$, $\beta_4^{\text{exp}} = -0.06$ and $\beta_5^{\text{exp}} = -0.05$).

The results of Model 2 (*model of perceptions*) indicate that only the first four SERVQUAL variables were positively related to the global satisfaction ($\beta_1^{\text{per}} = 0.27$, $\beta_2^{\text{per}} = 0.10$, $\beta_3^{\text{per}} = 0.30$

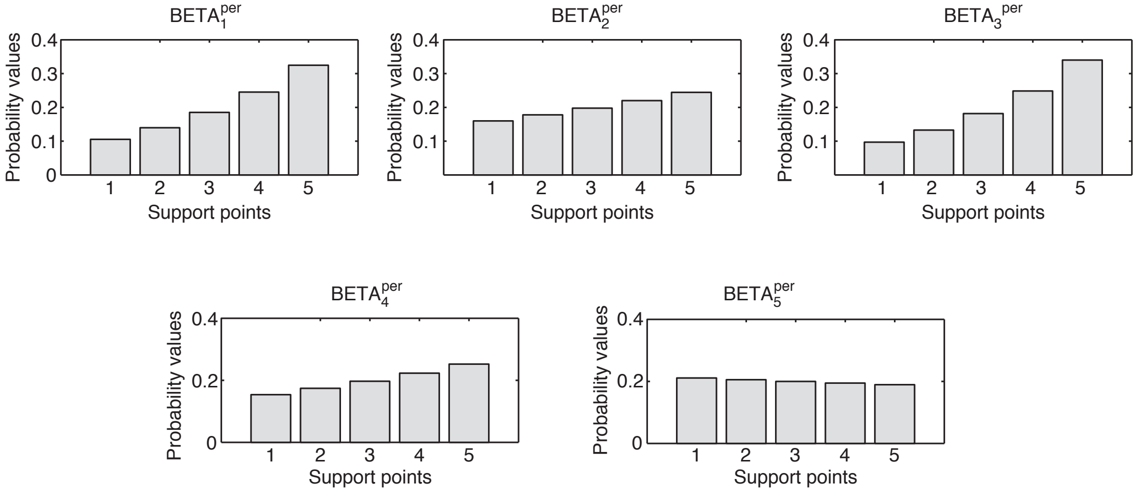

Figure 3. Model 2: probability distributions of the regression coefficients.

Table 3. Pseudo-R^2 for the four models analysed.

	Expectations	Perceptions	Cross-entropy	Differences
Pseudo-R^2	0.93	0.91	0.90	0.74

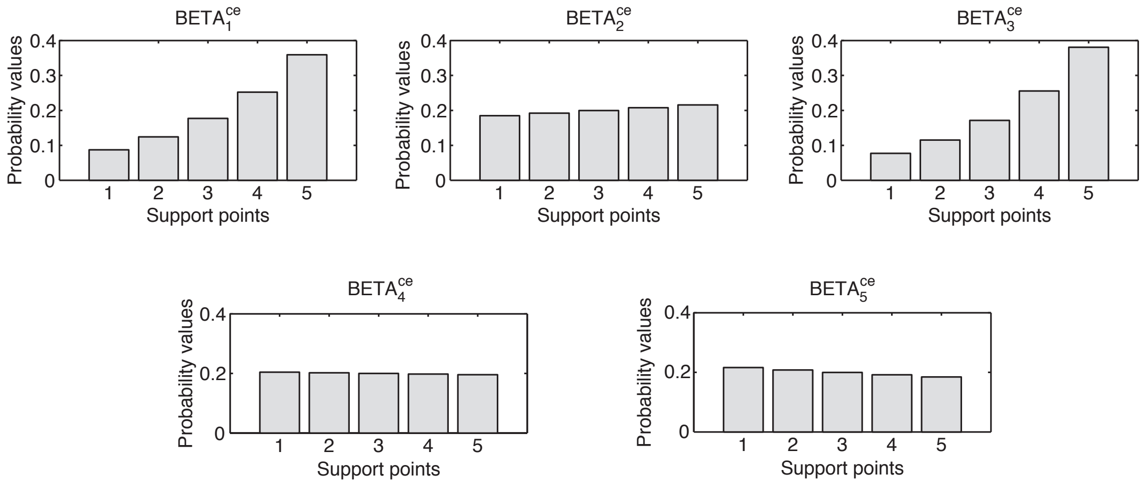

Figure 4. Model 4: probability distributions of the regression coefficients.

and $\beta_4^{\rm per} = 0.12$) whereas the fifth SERVQUAL variable had a negative, but very weak, relation with the dependent variable ($\beta_5^{\rm per} = -0.027$). In particular, the global satisfaction seemed to be strongly related to the responsiveness ($\beta_3^{\rm per} = 0.30$) and the tangibility ($\beta_1^{\rm per} = 0.27$) only. In general, the results of the first two models suggest that tangibility and responsiveness are two very relevant variables in the explanation of the global satisfaction.

The results of Model 3 (*model of differences*) showed that only tangibility, responsiveness and assurance were strongly related to the global satisfaction ($\beta_3^{dif} = -0.144$, $\beta_4^{dif} = -0.125$ and $\beta_4^{dif} = -0.125$). In general, this suggest that the higher the patients' expectation the lower their global satisfaction.

Finally, the results of Model 4 (*GCE-SERVQUAL*) showed that tangibility and responsiveness were the two variables which strongly related to the global satisfaction ($\beta_1^{ce} = 0.336$ and

$\beta_3^{ce} = 0.374$). In particular, these results suggest that the regression coefficients of tangibility and responsiveness are bigger than those ones estimated in the other models, which clearly do not use any prior information. In particular, they showed that the *greater the expectations the lower the satisfaction* and that perceptions increased according to the magnitude of the expectations. In such context, this may be interpreted as higher perceptions are really related to higher expectations. These suggestions can be also confirmed by looking Figure 4 where the distributions of tangibility and responsiveness are far away from the corresponding uniform distributions (which are, in turn, the baselines for such contrasts). The other SERVQUAL variables lost their importance considering their very low regression coefficients.

Tables 4–6 and Figure 4.4 show the results of the bootstrap procedure (Section 3.2.3) performed on our models ($Q = 5000$). For the sake of simplicity, we report the results for three models only (note that, Model 3 cannot be directly compared with our Model 4). In particular, for the Model 1 (*model of expectations*) all the variables are significant (see Table 5, first column) whereas, on the contrary, only four variables (β_1^{per}, β_2^{per}, β_3^{per} and β_4^{per}) are significant (see Table 6, second column) in the Model 2 (*model of perceptions*). Finally, also Model 4 (*GCE-SERVQUAL*) shows four significant variables (β_1^{ce}, β_2^{ce}, β_3^{ce} and β_5^{ce}), as we can notice in the third column of Table 6. In general, GCE-SERVQUAL seems to produce more accurate estimations than standard regression-based gap analyses (it shows low standard errors, see Table 6 and Figure 5), although the results did not reveal any differences among the models in terms of global fit (see Table 3).

5. Conclusions and further remarks

In this paper we proposed a novel method for SERVQUAL gap-analysis based on the GCE approach. According to the standard SERVQUAL model [37], the proposed GCE-SERVQUAL method allowed to take simultaneously into account expectations and perceptions within a unified model representation. In particular, the proposed method considered expectations as prior information and directly incorporate them in the estimation procedure. Moreover, GCE-SERVQUAL provided a peculiar two-step procedure thanks to which one can assess how the

Table 4. Bootstrap results: mean values and standard errors in parenthesis.

	Expectations	Perceptions	Cross-entropy
β_1	−0.388 (0.021)	0.273 (0.032)	0.327 (0.022)
β_2	0.064 (0.026)	0.102 (0.041)	0.041 (0.014)
β_3	−0.365 (0.028)	0.304 (0.031)	0.366 (0.030)
β_4	−0.065 (0.023)	0.120 (0.038)	−0.003 (0.021)
β_5	−0.058 (0.021)	−0.026 (0.026)	−0.037 (0.014)

Table 5. Bootstrap results: *t*-values.

	Expectations	Perceptions	Cross-entropy
β_1	−17.760	8.444	15.044
β_2	2.486	2.448	2.967
β_3	−13.117	9.863	12.368
β_4	−2.790	3.155	−0.152
β_5	−2.783	−1.031	−2.667

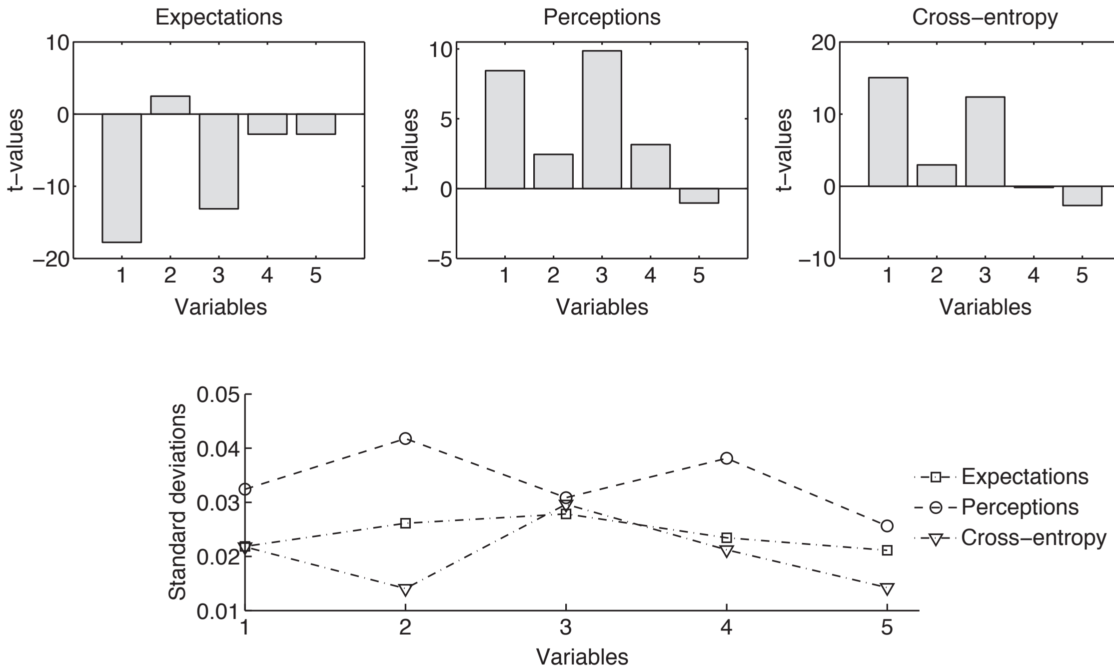

Figure 5. Graphical representation of the bootstrap results.

Table 6. Bootstrap results: p-values.

	Expectations	Perceptions	Cross-entropy
β_1	< 1e−03	< 1e−03	< 1e−03
β_2	0.013	0.014	0.003
β_3	< 1e−03	< 1e−03	< 1e−03
β_4	0.005	0.002	0.88
β_5	0.006	0.30	0.008

strength and direction of the perceptions can be augmented or diminished according to the expectations. To better illustrate the GCE-SERVQUAL characteristics, we also described a real Patient Satisfaction case study. The empirical results suggested that combining expectations and perceptions within a unified model is a more useful approach especially when researchers have to deal with SERVQUAL information.

However, the proposed method can potentially suffer from some limitations. For instance, in some empirical cases, standard SERVQUAL methodology cannot be valid and therefore other representation should be preferred (e.g. weighted-SERVQUAL models [30]). Moreover, some empirical contexts may require more complex data representation in order to adequately represent the real information (e.g. fuzzy data representation) and more sophisticated methods might occur (e.g. fuzzy-SERVQUAL method). Finally, an extensive Monte Carlo study would provide a substantial methodology for assessing the impact of some GCE parameters (such as, e.g. the number of support points, the choice of symmetric/asymmetric distributions) on the overall GCE-SERVQUAL results.

Different possible extensions of our proposal can be taken into account. For instance, the adoption of a weighted-GCE approach [29] would extend our proposal beyond the standard SERVQUAL approach. A future venue of research may also consist in the adoption of a fuzzy-based representation [10] in order to develop a system which can handle with non-random uncertainty presented in the empirical data. Finally, an organic and extensive Monte Carlo study may be performed in order to better understand the sample performances of the GCE parameters on SERVQUAL analyses. In addition, such simulation studies should consider a more general scenario which takes into account different models (e.g. low expectation/low satisfaction, low expectation/high satisfaction and high expectation/high satisfaction) for the expectation regression model.

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A. SERVQUAL Questionnaire used in the case study

Table A1. SERVQUAL questionnaire for patient satisfaction.

Tangibility	The hospital uses novel and serviceable instruments The hospital is well-functioning The medical personnel is neat
Reliability	The hospital personnel honour their promises for the service providing In case of problem or criticism, the hospital personnel was sympathetic The hospital personnel carefully give me information about the medical disease
Responsiveness	The hospital personnel is able to give information about the service The hospital personnel promptly supply the medical service The hospital personnel was always ready to supply the medical service
Assurance	The hospital personnel is able to be confident The hospital personnel is gear to give me information The hospital personnel was always kind The supervisors tend to give support to the hospital personnel in order to do right their work
Empathy	The hospital personnel focused on my-self The hospital personnel kept my personal interests
Global Satisfaction	Judgement about the hospital Judgement about the hospital personnel Judgement about the hospital nurses Judgement about the hospital machinery