A model for the integration of e-financial services questionnaires with SERVQUAL scales under fuzzy linguistic modeling

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ABSTRACT

Although it is habitual to measure human perceptions with quite accurate instruments, perceptions are characterized by uncertainty and fuzziness. Furthermore, variations in individual perceptions and personality mean that the same words can indicate very different perceptions. In this context, the fuzzy linguistic approach seems to be an appropriate framework for modeling information.

In this paper we explore the problem of integrating semantically heterogeneous data (natural language included) from various websites with opinions about e-financial services. We develop an extension of the fuzzy model based on semantic translation (FMST) under the perspective of the service quality (SERVQUAL) stream of research.

The model permits us to obtain a more precise representation of the opinions using each type of customers. By integrating all customers into different subsets, a financial entity can easily analyze the SERVQUAL characteristics over time or other dimensions owing to the easy linguistic interpretability and high precision of the results of the model.

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1. Introduction

In today's global conditions, firms and financial entities must now compete not only with internal organizations, but also with external firms (Büyüközkan & Çifçi, 2012). Furthermore, because of the significance and influence of service quality on service industries, as well as the difficulty in measuring service quality, many researchers have devoted much time to developing more generic instruments which could be widely employed to measure service quality and satisfaction across different service sectors. In many cases, companies use different survey methodologies and develop their own measurement scales to measure the same problem (online and offline).

In addition to traditional face-to-face surveys (PAPI, CAPI, HAPI), telephone surveys (CATI, TDE, VR, ASR) and self-administered surveys via mail or fax, Web surveys (CAWI, ACASI) have become increasingly common. The ease with which online questionnaires can be developed and administered, along with reduced costs for companies to collect data using these new tools, has flooded the market with surveys designed to measure consumer satisfaction.

This wide variety of surveying methods, however, makes it extremely difficult to compare results within the same company or between competing companies which operate in the same sector. It is therefore necessary to develop a tool to standardize survey results obtained with different methodologies, design proposals and measurement scales, and set time horizons. The objective of such a tool is to improve the interpretation and comparison of survey results and lend them far greater reliability when used by managers to support decision-making processes.

More concretely, these methods can be roughly categorized into two types: incident-based or attribute-based methods (Lin, 2010). Among the successive variants of the latter, the SERVQUAL instrument or service quality model (Parasuraman, Zeithaml, & Berry, 1985, 1988, 1991, 1994), also called the PZB model, is the most commonly used (Lin, 2010). SERVQUAL is a multiple-item scale for measuring five dimensions of service quality: *tangibles*, *reliability*, *responsiveness*, *assurance*, and *empathy*.

Several authors have adapted the SERVQUAL instrument to analyze electronic financial services expectations and perceptions about service quality (e.g., González, Mueller, & Mack, 2008; Han & Baek, 2004), but none have adopted a fuzzy linguistic approach. Some authors (Saleh & Ryan, 1991) propose a modified SERVQUAL with a basic questionnaire which presents customers with a collection of statements (questions) about the five above-mentioned

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dimensions to ask them if they are agree or disagree on a five-point Likert scale. This scale invention is attributed to Rensis Likert (Likert, 1931), who described this technique for the assessment of attitudes. McIver (McIver & Carmines, 1981) describes the Likert scale as a set of items made up of approximately an equal number of favorable and unfavorable statements concerning the attitude object, which is given to a group of subjects. They are asked to respond to each statement in terms of their own degree of agreement or disagreement. Typically, they are instructed to select one of five responses (five-point Liker scale): "strongly agree", "agree", "neutral", "disagree", or "strongly disagree".

In general, these human perceptions (expressed as natural language or a Likert scale) are characterized by uncertainty and fuzziness (Deng & Pei, 2009), that is, they are subjective and vague. Furthermore, variations in individual perceptions and personality mean that the same words can indicate very different perceptions (Chiou, Tzeng, & Cheng, 2005). Thus, because of their various experiences and individual preferences, customers normally have different opinions such as pessimistic, optimistic and neutral attitudes (Chin-Hung, 2008; Huynh, Nakamori, & Lawry, 2006). Consequently, the use of binary logic and crisp numbers to describe these human perceptions or attitudes (e.g., "strongly agree" = 2, "agree" = 1, "neutral" = 0, "disagree" = −1, and "strongly disagree" = −2) fails to address fuzziness (Zadeh, 1975). In this case, a better approach should be based on the use of linguistic assessments rather than numerical values.

The fuzzy linguistic approach was first introduced by Zadeh (1975). It is a tool intended to model qualitative information that has been used successfully in many domains and problems (e.g., Bordogna & Passi, 1993, 2001; Delgado, Verdegay, & Vila, 1992; Herrera-Viedma, 2001; Herrera-Viedma, López-Herrera, Luque, & Porcel, 2007; Yager, 1999). This approach is based on the concept of linguistic variables. Briefly speaking, linguistic variables are variables whose values are not numbers, but words or sentences in a natural or artificial language. Therefore, the fuzzy linguistic approach seems to be an appropriate framework for modeling the information like the one in which these human perceptions are used. Among these models, the fuzzy model based on semantic translation (FMST) introduced in Carrasco and Villar (2011) seems to be an appropriate framework for our problem due to its unique characteristics as described below:

- *The management of heterogeneous data* commonly included in the questionnaires, i.e., Likert scales, textual opinions and missing values described by trapezoidal membership functions. Several authors consider that these functions are good enough to capture the vagueness of the linguistic terms (Delgado et al., 1992).
- *High precision and good interpretability of the results.* Given an ordered set of primary linguistic terms specified with trapezoidal membership functions, the basic idea of the model consists in defining a semantic translation of such terms and then obtaining a more precise ordered set which includes the primary terms and the semantic translations of the terms. If we are aggregating the age of customers, the result could be, for example, "*teenager –* 2" with the linguistic interpretability "2 years to *teenager*".

In this paper we present a model for integrating heterogeneous e-financial services questionnaires based primarily on the FMST. The final goal is to determine the overall opinion of a community on some e-financial services under the perspective of the SERV-QUAL instrument. The heterogeneous data (natural language included) was drawn from various web or online questionnaires.

The rest of the paper is structured as follows. Section 2 reviews the preliminary concepts including the FMST and the SERVQUAL scale. Section 3 presents the new model, or linguistic integration process, which is carried out in four steps. Section 4 presents a case

study on service quality and customer satisfaction with an e-banking system of a Spanish savings bank. Finally, concluding remarks are made and future research lines are proposed.

2. Preliminaries

In this section we present the basic elements needed to understand our new proposal: the fuzzy linguistic approach, the FMST as a tool to obtain a linguistic summarization and the SERVQUAL scale.

2.1. The fuzzy linguistic approach

Since the concept was introduced (Zadeh, 1975), linguistic variables have been widely used. Briefly speaking, *linguistic variables* are variables whose values are sentences in a natural or artificial language. The values of linguistic variables are called *linguistic labels*. In more specific terms, a linguistic variable is characterized by a quintuple $\langle H, T(H), U, G, M \rangle$ in which:

- H is the name of the variable.
- $T(H)$ is the term-set of H or the collection of linguistic values (*labels*).
- U is the universe of discourse.
- G is the syntactic rule, i.e., a context-free grammar which generates the terms in $T(H)$.
- M is the semantic rule which defines the meaning of each linguistic label X, $M(X)$, where $M(X)$ denotes a fuzzy subset of U.

The fuzzy linguistic approach (Zadeh, 1975) is a tool used for modeling qualitative information in a problem. It is based on the concept of linguistic variables and has been satisfactorily used in some problems such as information retrieval (Bordogna & Passi, 1993, 2001; Herrera-Viedma, 2001; Herrera-Viedma et al., 2007), decision-making (Delgado et al., 1992; Yager, 1999) or the complexity in the implementation of services via Internet (e.g., Lin, 2010 [regular chain supermarket]; Awasthi, Chauhan, Omrani, & Panahi, 2011 [transportation]; Chou, Liu, Huang, Yih, & Han, 2011 [airplane]; Büyüközkan & Çifçi, 2012 [healthcare]). We have to choose the appropriate linguistic descriptors for the term set and their semantics. In order to accomplish this objective, an important aspect to analyze is "granularity of uncertainty", that is, the level of discrimination among different counts of uncertainty. Typical values of cardinality used in the linguistic models are odd ones, such as 5 or 7, where the midterm represents an assessment of "approximately 0.5", and with the rest of the terms being placed symmetrically around it (Bonissone & Decker, 1986). Once the cardinality of the linguistic term set has been established, the linguistic terms and its semantics must be provided as follows:

- Generation *of the linguistic terms.* There are primarily two ways to accomplish this task (Bonissone, 1982; Bordogna & Passi, 1993; Yager, 1995). One of them involves directly supplying the term set by considering all the terms distributed on a scale on which a total order is defined (Herrera, Herrera-Viedma, & Verdegay, 1995; Yager, 1995). The other, following Bordogna and Passi (1993), is to specify a context-free grammar G defined by the 4-tuple $\langle V_T, V_N, P, I \rangle$ where:

  1. V_T is the set of the terminal symbols, also called the alphabet.
  2. V_N is the set of nonterminal symbols.
  3. P is the set of the production rules.
  4. I is the start symbol or axiom.

- *Semantic of the linguistic terms*. Often, the semantics of the terms are represented by fuzzy numbers defined in the interval [0,1] and described by membership functions. One way to characterize a fuzzy number is to use a representation based on parameters of its membership function (Bonissone & Decker, 1986). The linguistic assessments given by the users are only approximate. Some authors consider that linear trapezoidal membership functions are good enough to capture the vagueness of such linguistic assessments (Delgado et al., 1992). The parametric representation is achieved by the 4-tuple $[\alpha, \beta, \gamma, \delta]$ where β and γ indicate the interval in which the membership value is 1, with α and δ indicating the left and right limits of the definition domain of the trapezoidal membership function (Bonissone & Decker, 1986).

In what follows we analyze Carrasco and Villar's (2011) fuzzy linguistic model that is used in our system.

2.2. Linguistic summarization using the fuzzy model based on semantic translation

We now proceed to explain the representation and computational model of FMST (Carrasco & Villar, 2011). We then define a new linguistic aggregation operator based on the approximative computational model (Bonissone & Decker, 1986) that overcomes the main drawback of this model, namely the loss of information caused by the need to express the results in the initial expression domain. With this new operator, FMST is proposed as a tool to obtain a linguistic summarization.

2.2.1. The fuzzy representation model based on semantic translation

Let $S = \{s_i\}, i \in \{0, \ldots, g\}$ be a linguistic term set, such that each term s_i is associated to the semantic of the trapezoidal membership function $[\alpha_i, \beta_i, \gamma_i, \delta_i]$. Let the fuzzy operator be $\sigma: S \times S \rightarrow [0,1]$ such that $\forall s_i, s_j \in S$, $\sigma(s_i, s_j)$ represents *fuzzy degree of superiority of s_i over s_j*. We demand that the operator σ forms a total order relation on S, i.e., $\forall s_i, s_j \in S$ if $\sigma(s_i, s_j) > \sigma(s_j, s_i) \Longleftrightarrow i > j$. There are many possible ways to define the operator σ over $A = [\alpha_A, \beta_A, \gamma_A, \delta_A]$ and $B = [\alpha_B, \beta_B, \gamma_B, \delta_B]$ (two trapezoidal possibility distributions, see Fig. 1): possibility and necessity theory (see Table 1) or even the subjective criterion of some decision maker (Carrasco, Galindo, & Vila, 2001), among others.

Definition 1. We define these *semantic translations of a term $s_i \in S$*, as $s_i + d_i = [\alpha_i + d_i, \beta_i + d_i, \gamma_i + d_i, \delta_i + d_i]$, with $d_i \in D_{STi} = \{d: d \in [-\underline{d}_i, \overline{d}_i]\}$, where $\overline{d}_i$ and $\underline{d}_i$ are, respectively, the *maximum* and *minimum* value of the translation of a term s_i based on an operator σ and a threshold χ defined as:

$$\overline{d}_i = \begin{cases} 0, & \text{if } i = g \\ \text{Sup}\{d \in U : \sigma(s_{i+1}, s_i - 2 \times d) > \chi\}, \\ & \text{otherwise} \end{cases}$$

$$\underline{d}_i = \begin{cases} 0, & \text{if } i = 0 \\ \text{Sup}\{d \in U : \sigma(s_i - 2 \times d, s_{i-1}) \geqslant \chi\}, \\ & \text{otherwise} \end{cases}$$

We call d_i *the value of translation of s_i* and it represents the "semantic difference of information" between $s_i + d_i$ and s_i. From Definition 1, we have semantic consistence on S regarding the previous order relation, i.e., we can conclude that $\forall s_{j-1}, s_j, s_{j+1} \in S, j \in \{1, \ldots, g-1\}$ *fulfils*: $\sigma(s_j - \underline{d}_j, s_{j-1} + \overline{d}_{j-1}) > \chi$ and $\sigma(s_{j+1} - \underline{d}_j, s_j + \overline{d}_{j-1}) > \chi$.

Let h be a natural *number* in order to define a grammar that generates a finite set of terms, we obtain a discrete set from D_{STi}. Thus, let D_{HSTi} be the set of the *h-higher semantic translations of a*
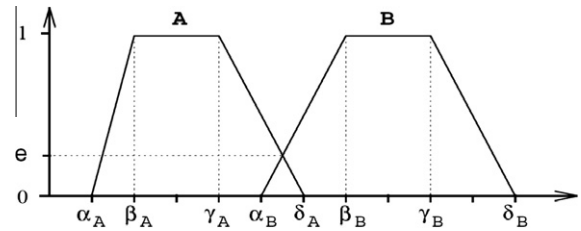

Fig. 1. Possibility operator definition $\varepsilon(A,B) = e$.

Table 1
Examples of definition of the operator σ.

Possibility operator definition σ		Necessity operator definition σ	
$= 1$	if $\gamma_A \geqslant \delta_B$	$= 1$	if $\alpha_A \geqslant \delta_B$
$= \frac{\delta_A - \gamma_B}{\delta_B - \gamma_B - (\gamma_A - \delta_A)}$	if $\gamma_A < \delta_B \& \delta_A > \gamma_B$	$= \frac{\beta_A - \gamma_B}{\delta_B - \gamma_B - (\alpha_A - \beta_A)}$	if $\gamma_A < \delta_B \& \beta_A > \gamma_B$
$= 0$	otherwise	$= 0$	otherwise

term s_i defined as $D_{HSTi} = \{\overline{d}'_{ij} : \overline{d}'_{ij} = j \times \overline{d}_i / h\}, \forall j \in \{1, \ldots, h\}$; and let D_{LSTi} be the set of the *h-lower semantic translations of a term s_i* defined as $D_{LSTi} = \{\underline{d}'_{ij} : \underline{d}'_{ij} = (-j + h + 1) \times \underline{d}_i / h\}, \forall j \in \{1, \ldots, h\}$.

Now we proceed to define the representation model as a set of the production rules defined in an extended Backus Naur Form in which the square brackets enclose optional elements, the symbol $*$ indicates the possible repetition of the elements which follow, and the symbol | indicates alternative elements.

Definition 2. The representation of the model based on the semantic translation is generated from the context-free grammar G where $\forall i \in \{0, \ldots, g\}$ and $\forall j \in \{0, \ldots, h-1\}$:

```
V_T = s_i
V_N={<term>, <low comp term>, <hig comp term>, <trans
   low>, <trans hig>}
P=<term>::= {<low comp term>|<primary term>|<hig
   comp term>}
    <low comp term>::=*[<primary term><trans low>]
    <trans low>::= <sign trans low>{d'_ij|d'_ij|⋯|d'_ij}
    <hig comp term>::=*[<primary term><trans hig>]
    <trans hig>::= <sign trans hig> {d'_ij|d'_ij|⋯|d'_ij}
    <primary term>::= s_i
    <sign trans low>::= ''−''
    <sign trans hig>::= ''+''
I = <term>
```

Therefore, each <primary term> has associated with it the semantic of a trapezoidal membership function; and each <hig comp term> and <low comp term> have associated the semantic of the <primary term> with a difference of information of <trans hig> (higher) and <trans low> (lower), respectively.

2.2.2. The fuzzy computational model based on semantic translation

The grammar G has led to the definition of a new ordinal set $\widehat{S} = \{s_0, s_0 + \overline{d}'_{01}, \ldots, s_0 + \overline{d}'_{0h}, \ldots, s_g - \underline{d}'_{g1}, \ldots, s_g - \underline{d}'_{gh}, s_g\}$. Given that the primary terms have the semantic translation 0, we will proceed to rename the set as $\widehat{S} = \{s_0 + 0, s_0 + \overline{d}'_{01}, \ldots, s_0 + \overline{d}'_{0h}, \ldots, s_g - \underline{d}'_{g1}, \ldots, s_g - \underline{d}'_{gh}, s_g + 0\}$. Therefore, $\widehat{S} = \{s_i + d_i\}, i \in \{1, \ldots, m\}$ and $m = (2 \times h + 1) \times (g - 1)$; and if each term $s_i + d_i$ is renamed as $\hat{s}_i$ we have that $\widehat{S} = \{\hat{s}_i\}, i \in \{1, \ldots, m\}$. We can also conclude that the operator σ forms a total order relation on $\widehat{S}$.

We will define the computer model on this new set. This model will be more accurate as the number of semantic translations (h) is greater.

The comparison of terms is carried out according to the ordinary lexicographic order of $\widehat{S}$, i.e., $\forall \hat{s}_k, \hat{s}_l \in \widehat{S}$ if $k < l \Longleftrightarrow \hat{s}_k < \hat{s}_l$. Therefore, the maximization operator is $max(\hat{s}_k, \hat{s}_l) = \hat{s}_l \Longleftrightarrow \hat{s}_k < \hat{s}_l$; and the minimization operator is $min(\hat{s}_k, \hat{s}_l) = \hat{s}_k \Longleftrightarrow \hat{s}_k < \hat{s}_l$.

The aggregation of information consists of obtaining a value that summarizes a set of values. Yager (1988) introduced the *Ordered Weighted Averaging* (OWA) operator. A fundamental aspect of the OWA operator is the reordering of the arguments to be aggregated based upon the magnitude of their respective values:

Definition 3. An OWA operator of dimension n is a function $\varphi : \Re^n \to \Re$, which has a set of associated weighting vectors $W = \{w_j\}$, $j \in \{1, \ldots, n\}$, $w_j \in [0,1]$. It is defined to aggregate a list of values $P = \{p_j\}, j \in \{1, \ldots, n\}, p_j \in \Re$ according to the following expression: $\varphi(p_1, \ldots, p_n) = \sum_{i=1}^{n} w_i p_{\sigma(i)} / \sum_{j=1}^{n} w_j$ where $\rho : \{1, \ldots, n\} \to \{1, \ldots, n\}$ is a permutation such that $p_{\rho(i)} \geqslant p_{\rho(i+1)}, \forall i = 1, \ldots, n-1$, i.e., $p_{\rho(i)}$ is the i-th highest value in the set P.

In our problem, let $A = \{a_j\}, j \in \{1, \ldots, n\}$, and $a_j \in S$ be a set of terms to aggregate described by trapezoidal membership functions where $a_i = [\alpha_{aj}, \beta_{aj}, \gamma_{aj}, \delta_{aj}]$; W is their associated weights; and B is the associated ordered term vector. Each element $b_i \in B$, defined as $b_i = [\alpha_{bi}, \beta_{i}$ $_i = [\alpha_{bi}, \beta_{bi}, \gamma_{bi}, \delta_{bi}]$, is the ith largest term in the collection ordered vector $\{a_1, \ldots, a_n\}$. Additionally, let the fuzzy operator $\varepsilon : S \times S \to [0,1]$ be such that $\forall s_i, s_j \in S, \varepsilon(s_i, s_j)$ represents *the fuzzy degree of equality of s_i over s_j*. There are several possible ways to define the operator ε over A and B (two trapezoidal possibility distributions): possibility and necessity theory (see Table 2), the subjective criterion of some decision maker (Carrasco et al., 2001), among others.

Before defining the aggregation operators, we define the following:

Definition 4. We define the *fuzzy degree of equality of $\hat{s} \in \widehat{S}$ over an ordered set of terms B weighted by W based on an operator ε*:

$$\Theta^{OWA,}(\hat{s}, B, W) = \sum_{j=1}^{n} \varepsilon(\hat{s}, b_j) \times w_j$$

Now we proceed to define the aggregation operator:

Definition 5. Let $\Theta^{SupOWA,}(\widehat{S}, B, W) = \text{Sup}\{\Theta^{OWA,}(\hat{s}_i, B, W), \forall i \in \{1, \ldots, m\}\}$. We define the average over an ordered set of terms B weighted by W based on an operator ε with respect to $\widehat{S}$ as follows:

$$\Theta^{LOWA,}(\widehat{S}, B, W) = \begin{cases} \hat{s} = \hat{s}_j, \text{ if } \exists \hat{s}_j, \hat{s}_k \in \widehat{S}.j, k \in \{1, \ldots, n\} \text{ and } j \neq k: \\ \Theta^{OWA,}(\hat{s}_j, B, W) = \Theta^{OWA,}(\hat{s}_k, B, W) = \Theta^{SupOWA,}(\widehat{S}, B, W) \text{ and} \\ |d_j| < |d_k| \\ \hat{s} \in \widehat{S} : \Theta^{OWA,}(\hat{s}, B, W) = \Theta^{SupOWA,}(\widehat{S}, B, W), \text{ otherwise} \end{cases}$$

We call the *degree of representativeness* of $\Theta^{LOWA,}(\widehat{S}, B, W)$ operator to a value in [0,1] defined as: $\Theta^{RepOWA,}(\widehat{S}, B, W) = \Theta^{SupOWA,}(\widehat{S}, B, W) / \sum_{j=1}^{n} w_j$. Therefore, if the degree of representativeness is the same for more than one term, we choose the term with less semantic translation (in absolute values) in order to define the operator $\Theta^{LOWA,}$. This degree should be close to the value of 1 for an acceptable representativeness of the chosen term $\Theta^{LOWA,}(\widehat{S}, B, W)$.

2.2.3. The fuzzy computational model based on semantic translation using the approximative computational model

The approximative computational model based on the Extension Principle (Bonissone & Decker, 1986) uses fuzzy arithmetic based on the Extension Principle to make computations over the linguistic variables. A linguistic aggregation operator based on this model acts according to: $S^n \xrightarrow{\Im} F(\Re R) \xrightarrow{app_1(\bullet)}$, where S^n symbolizes the

Table 2
Examples of definition of the operator ε.

Possibility operator definition ε	Necessity operator definition ε
$= \sup_{d \in U} \min(A(d), B(d))$ where U is the domain of A, B. $A(d)$ is the degree of the possibility for $d \in U$ in the distribution A (see Fig. 1)	$= \inf_{d \in U} \max(1 - A(d), B(d))$ where U is the domain of A, B. $A(d)$ is the degree of the possibility for $d \in U$ in the distribution A

n Cartesian product of S, $\Im$ is an aggregation operator based on the extension principle, $F(\Re)$ is the set of fuzzy sets over the set of real numbers, and $app_1(\bullet)$ is a linguistic approximation function that returns a label from the linguistic term set S whose meaning is the closest to the unlabeled fuzzy number obtained. The main drawback of this model is the loss of information caused by the need to express the results in the initial expression domain. However, we can obtain much more accurate results if we express the results using the set $\widehat{S}$ instead of S. Based on this idea, we proceed to define the new aggregation operator:

Definition 6. Let $\Im = [\varphi(\alpha_{a1}, \ldots, \alpha_{an}), \varphi(\beta_{a1}, \ldots, \beta_{an}), \varphi(\gamma_{a1}, \ldots, \gamma_{an}), \varphi(\delta_{a1}, \ldots, \delta_{an})]$ be an aggregation operator based on the OWA operator (Definition 3); and let $\Theta^{SupOWA,}(\Im, \widehat{S}) = \text{Sup}\{\Theta^{OWA,}(\Im, \hat{s}_j, \{1\}), \forall j \in \{1, \ldots, n\}\}$. We define the average over an ordered set of terms B weighted by W based on an operator ε with respect to $\widehat{S}$ as follows:

$$\Theta^{LOWA,}(\widehat{S}, B, W) = \begin{cases} \hat{s} = \hat{s}_j, \text{ if } \exists \hat{s}_j, \hat{s}_k \in \widehat{S}.j, k \in \{1, \ldots, n\} \text{ and } j \neq k: \\ \Theta^{OWA,}(\Im, \hat{s}_j, \{1\}) = \Theta^{OWA,}(\Im, \hat{s}_k, \{1\}) = \Theta^{SupOWA,} \\ (\Im, \widehat{S}) \text{ and } |d_j| < |d_k| \\ \hat{s} \in \widehat{S} : \Theta^{OWA,}(\Im, \hat{s}, \{1\}) = \Theta^{SupOWA,}(\Im, \widehat{S}), \text{ otherwise} \end{cases}$$

We call the *degree of representativeness* of $\Theta^{LOWA,}(\widehat{S}, B, W)$ operator to a value in [0,1] defined as: $\Theta^{RepOWA,}(\widehat{S}, B, W) = \Theta^{OWA,}(\hat{s}, B, W) / \sum_{j=1}^{n} w_j$. As in Definition 5, if the degree of representativeness is the same for more than one term, we choose the term with less semantic translation (in absolute values) in order to define the operator $\Theta^{LOWA,}$. This degree should be close to the value of 1 for an acceptable representativeness of the chosen term.

2.2.4. Linguistic data summaries

The current growth of information technology has led to the availability of a huge amount of data. Unfortunately, the greater availability of data does not mean that the data are more useful or productive. Data summarization attempts to reduce facts to knowledge to aid in decision making. The linguistic summary can be viewed as a natural language-like sentence that subsumes the very essence (from a certain point of view) of a set of data (Kacprzyk & Yager, 2001; Laurent, 2003; Yager, 1982, 1991). This set is assumed to be generally large and incomprehensible in its original form by human beings. Often, the following context for linguistic summaries mining is assumed:

- $Y = \{y_1, \ldots, y_{\#Y}\}$ is a set of objects (records) in a database, e.g., the set of a bank customers; where $\# Y \geqslant 1$ is the cardinality of the set Y;
- $R = \{r_1, \ldots, r_{\#R}\}$ is a set of attributes characterizing objects from Y, e.g., "age", in a database, $y_i(r_j), i \in \{1, \ldots, \#Y\} j \in \{1, \ldots, \#R\}$ denotes a value of attribute r_j for object y_i, and $Y(r_j)$ denotes the set $\{y_i(r_j)\}$.

Yager (Yager, 1982; Yager, 1991; Kacprzyk & Yager, 2001) proposed that a linguistic summary of data set Y for an attribute r_j, $\mathscr{S}r_j^Y$, can be made in terms of three values $\left\langle sr_j^Y, Qr_j^Y, Tr_j^Y \right\rangle$:

- A *summarizer* $sr_j^Y \in Sr_j$, i.e., an attribute together with a linguistic value (fuzzy predicate) defined on the domain of attribute r_j (e.g., "young" for attribute r_j = "age"). The set Sr_j contains all the possible linguistic terms defined for the attribute r_j.
- A *quantity in agreement* Qr_j^Y, i.e., a linguistic quantifier. Linguistic quantifiers (Galindo, Carrasco, & Almagro, 2008) allow us to express fuzzy quantities or proportions in order to provide an approximate idea of the number of elements of a subset fulfilling a certain condition or the proportion of this number in relation to the total number of possible elements. Linguistic quantifiers can be *absolute* or *relative*. Some examples for absolute are "much more than 100", "close to 100", and for relative "a great number of", "the majority" or "most", "the minority", etc. Therefore, Qr_j^Y, is a proposed indication of the number of pieces of $Y(r_j)$ that satisfy sr_j.
- *Truth* (validity) Tr_j^Y *of the summary*, i.e., a number from the interval [0, 1] assessing the truth (validity) of the summary (e.g., 0.7). Usually, only summaries with a high value of Tr_j^Y are interesting. Thus, the linguistic summary may be exemplified by " Tr_j^Y (most bank customers are young) = 0.7".

In order to obtain $\mathscr{S}r_j^Y$ using the FMST, a procedure is proposed in Carrasco and Villar (2011) with the primary aim of using the more precise set $\widehat{S}$ obtained from S.

2.3. The SERVQUAL scale

The SERVQUAL scale is a survey instrument which claims to measure service quality in any type of service organization. The scale was originally proposed by Parasuraman et al. (1985). They conducted in-depth interviews with executives of service firms and customer focus groups, and then defined service quality as the gap between perceptions and expectations of customers, which is referred to as the *P–E gap*. Initially, a multiple-item scale for measuring ten dimensions of service quality was proposed. The scale was later simplified to five dimensions in 1988 (Parasuraman, Zeithaml, & Berry, 1988). In memory of Parasuraman, Zeithaml, and Berry, the method was named the PZB model. Further improvements to SERVQUAL were made in 1991 (Parasuraman, Zeithaml, & Berry, 1991) and 1994 (Parasuraman, Zeithaml, & Berry, 1994).

Ladhari (2009) reviewed the different applications of the SERVQUAL scale from 1988 to 2008, highlighting the increasing importance of online services in society if it is true that there is still much literature. This scale was created to measure service quality in a traditional service context (offline). However, with the successive technological innovations that have been developed in recent years, the applicability of this scale has also been considered in online environments. Several authors have incorporated changes to the original measurement scale to develop new scales (Zeithaml, Parasuraman, & Malhotra, 2000, 2002 [e-SERVQUAL]; Loiacono et al., 2000, Loiacono, Watson, & Goodhue, 2007 [WEBQUAL]; Janda, Trocchia, & Gwinner, 2002 [IRSQ]; Parasuraman, Zeithaml, & Malhotra, 2005 [ES-QUAL]; Cristobal, Flavian, & Guinaliu, 2007 [PESQ]; Lin, 2011 [SSTQUAL]).

The banking sector has also been the object of traditional service quality analyses (Bahia & Nantel, 2000; Bath, 2005; Fernández-Barcala, 2000; Jayawardhena, 2004; Kumar, Kee, & Manshor, 2009; Ladhari, Ladhari, & Morales, 2011; Rajesh, Ranjith, Sumana, & Charu, 2010; Saurina, 2002). Our research, however, will focus on e-banking or e-financial services. Concretely, we explain the five dimensions proposed for the SERVQUAL instrument and their adaptations to e-services perceptions (Ladhari, 2009; Parasuraman et al., 1985):

- *Tangibles:* The appearance of physical facilities or equipment (in our case the interface of the financial website), ease to operate the services, and accessibility (Han & Baek, 2004; Wu, Tao, & Yang, 2010; Zhou, Zhang, & Ji, 2010) and agility of operations (Han & Baek, 2004; Wu et al., 2010).
- *Reliability:* The ability to perform the promised service dependably and accurately, i.e., the reliability of operations (Han & Baek, 2004; Jun & Cai, 2001; Khan & Mahapatra, 2009; Wu et al., 2010; Yang, Jun, & Peterson, 2004; Zhou et al., 2010).
- *Responsiveness:* The willingness to help customers and provide prompt service, i.e., customer attention (Han & Baek, 2004; Jun & Cai, 2001; Khan & Mahapatra, 2009; Wu et al., 2010; Yang et al., 2004; Zhou et al., 2010).
- *Assurance:* The level of protection of confidential information, the security of the operations (Brasil, Garcѧa, & Antonialli, 2006; Han & Baek, 2004; Khan & Mahapatra, 2009; Wu et al., 2010; Yang et al., 2004; Zhou et al., 2010) and their ability to inspire trust and confidence.
- *Empathy:* The level of caring, usefulness, actualization of information (Brasil et al., 2006) and suitability to the needs of uses of the system (Brasil et al., 2006; Han & Baek, 2004; Zhou et al., 2010).

Moreover, some of these authors (Saleh & Ryan, 1991) propose a modified version of SERVQUAL with a basic questionnaire that presents customers with a series of statements (questions) about the five above-mentioned scales to ask them if they agree or disagree on a five-point Likert scale. In order to obtain a more simplified model in this paper, we will use this five-point Likert scale form type based on customers' perceptions.

Furthermore, e-financial services questionnaires often ask customers about the overall assessment of the service (Zhou et al., 2010). Since we consider such assessments to be very important, we propose that they be included as a new scale, similar to the one proposed for other quality evaluations models such as the course experience questionnaire (McInnis, Griffin, James, & Coates, 2001):

- *Overall Satisfaction Index (OSI):* This index indicates customers overall satisfaction level with respect to the e-service.

3. Linguistic integration of heterogeneous e-financial services questionnaires

In this section, we show a model for aggregating heterogeneous questionnaires based mainly on the FMST explained in Section 2. The final goal is to determine the overall opinion of a community on some e-financial services under the perspective of the SERVQUAL instrument, that is, the SERVQUAL quality evaluation value of such services.

Although these opinions have been provided by different populations in diverse websites, they have several common features (dimensions) such as time (month, year, etc.) and space (country, region, etc.), among others. The objective is to aggregate these opinions into the five-point Likert SERVQUAL scale proposed in Section 2.2, which characterizes them according to their common features.

We have applied the following formal framework to the problem we are attempting to solve: Let $R = \{R_1, \ldots, R_{\#R}\}$ be a collection of non-empty sets of questions on e-financial services, i.e., questionnaires to be aggregated (input questionnaires), where $\#R \geqslant 1$ is the cardinality of the set R. Let each questionnaire $R_a = \{r_{a,1}, \ldots, r_{a,\#Ra}\}$, $\forall a \in \{1, \ldots, \#R\}, \#R_a \geqslant 1$ be a set of $\#R_a$ questions. Let $PZB = \{pzb_1, \ldots, pzb_n\}, n = 6$ be a questionnaire based on the

SERVQUAL scale with five-point Likert type questions: pzb_1 = Tangibles, pzb_2 = Reliability, pzb_3 = Responsiveness, pzb_4 = Assurance, pzb_5 = Empathy and pzb_6 = Overall Satisfaction Index. Assuming that we have several groups of customers (decision makers) $Y = Y_1 \cup \cdots \cup Y_{\#R}, Y_a = \{y_{a,1}, \ldots, y_{a,\#Ya}\}, \#Y_a \geqslant 1$, which have filled out the corresponding questionnaires R_a, we consider that $Y_a(r_{a,b}) = \{y_{a,c}(r_{a,b})\}$, $\forall b \in \{1, \ldots, \#R_a\}$ and $\forall c \in \{1, \ldots, \#Y_a\}$ contain the opinions provided by the customers $y_{a,c}$ on subjective criteria represented by the question $r_{a,b}$. The objective is to obtain a unique PZB type form, $PZB_o = \{pzb_{o,1}, \ldots, pzb_{o,n}\}, n = 6$, with the integrated answers to the input questionnaires, i.e., $Y_a(r_{a,b})$, $\forall a \in \{1, \ldots, \#R\}$, $\forall b \in \{1, \ldots, \#R_a\}$. With this purpose, we propose a model that consists of the following steps (see Fig. 2).

We now proceed to explain each of these steps in more detail.

3.1. The choice of the initial linguistic domains

The choice of the linguistic term set with its semantics is the first goal to fulfill in any linguistic approach for solving a problem (Herrera & Herrera-Viedma, 2000). This consists of establishing the linguistic variable (see Section 2.1) or linguistic expression domain with a view to providing the linguistic performance values for the responses in the questionnaires. This definition is given for each of the questions of the input and output questionnaires in order to describe these human perceptions or attitudes as linguistic performance values. As universe of discourse U, we consider the commonly used interval [0,10] and then specify the initial domains for:

- *PZB questionnaire.* As mentioned in Section 2.3, a five-point Likert scale is used for the output questionnaire of our system. The five-point Likert scale is a set of items made up of an equal number of favorable and unfavorable statements concerning the attitude object. It is provided to a group of subjects who are instructed to select one of five possible responses: "strongly agree", "agree", "neutral", "disagree", or "strongly disagree". We consider the possibility shown in Section 2.1, which defines the linguistic expression domain by means of an ordered set of linguistic terms. We then characterize the initial linguistic expression domains as follows:
  - The granularity value is 5.
  - We consider a linguistic term set on which a total order is defined and distributed with the midterm representing an assessment of "neutral", with the rest of the terms being placed symmetrically around it.

Fig. 2. Linguistic integration process input questionnaires into a SERVQUAL form.

- We define the semantics by considering that each linguistic term for the pair (s_i, s_{g-i}) ($g + 1$ is the cardinality, i.e., 5) is equally informative and by assigning trapezoidal membership functions to each linguistic term.
- Thus, we can use the set of five linguistic terms shown in Fig. 3 for each domain: $S = Spzb_1 = \cdots = Spzb_n = \{s_0, \ldots, s_g\}$, $g = 4$: s_0 = Strongly Disagree (SD), s_1 = Disagree (D), s_2 = Neutral (N), s_3 = Agree (A), and s_4 = Strongly Agree = (SA).

- *Input questionnaires.* Due to the heterogeneous information of the questionnaires, we have identified the following frequent linguistic domains: $Sr_{a,b} = \{s_{a,b,0}, \ldots, s_{a,b,\#Sra,b}\}, \#Sr_{a,b} \geqslant 1$, for the questions $r_{a,b}$ for which the FMST is directly usable since they can be expressed with trapezoidal possibility distributions (Carrasco & Villar, 2011):
  - *n-Likert scales* with the above remarks for the five-point scale. This can also be expressed as numerical terms with associated linguistic labels, e.g., for an eleven-point scale: $L00 = 0$, $L01 = 1$, etc. Fig. 4 shows an option to define this eleven-point Likert scale.
  - *Missing and undefined values* are specified as a trapezoidal function (see, for example, Umano & Fukami, 1994): Unknown = UNK, defined as [1,1,1,1], or Undefined = UND, defined as [0,0,0,0].
  - *Linguistic terms included in text opinions.* Often a large portion of users do not provide feature ratings. In this case, the opinions expressed by these users of e-financial services in natural language are an important source of information. Therefore, we propose obtaining the value of the service features from the customers' textual opinions, and we express it as a term of the set $Sr_{a,b}$ previously defined by the data analysts. We propose obtaining the pair of features $(r_{a,b})$ and ratings $\{y_{a,c}(r_{a,b})\}$ using a text mining schema. Oracle Text© (Dixon, 2001; Shea, 2008) is proposed as a tool for the text mining process to manage comments in English and Spanish language. In particular, we use the *contains* operator (Shea, 2008) in combination with the *near* operator (Shea, 2008) to return a score based on the proximity of the two search terms (characteristic and rating). In order to search both terms, we use a specific thesaurus of terms that contains synonyms of $Sr_{a,b}$ terms (including formal and informal terms and abbreviators); higher-level terms; and words that have the same root as the specified term (using the *stem* operator; Shea, 2008). We also use a helpful operator to find more accurate results when there are frequent misspellings in the opinion text including words that sound like the specified terms (*soundex* operator; Shea, 2008) and words that are spelled similarly to the specified terms (*fuzzy* operator; Shea, 2008).

3.2. The definition of the FMST

In this phase, we define the representation and computational model for all the domains of our problem:

- *Definition of the representation model of the FMST.* We define the set $$\hat{S} = \{s_0, s_0 + \mathbf{d}'_{01}, \ldots, s_0 + \mathbf{d}'_{0h}, \ldots, s_g - \underline{\mathbf{d}}'_{g1}, \ldots, s_g - \underline{\mathbf{d}}'_{gh}, s_g\}$$ from the set S (output domain), and the sets

$$\hat{Sr}_{a,b} = \{s_{a,b,0}, s_{a,b,0} + \mathbf{d}'_{a,b,01}, \ldots, s_{a,b,0} + \mathbf{d}'_{a,b,0h}, \ldots, s_{a,b,\#Sra,b} \\ - \underline{\mathbf{d}}'_{a,b,\#Sra,b1}, \ldots, s_{a,b,\#Sra,b} - \underline{\mathbf{d}}'_{a,b,\#Sra,bh}, s_{a,b,\#Sra,b}\}$$

from the sets $Sr_{a,b}$ (input domains), $\forall a \in \{1, \ldots, \#R\}$, and $\forall b \in \{1, \ldots, \#R_a\}$, correspondingly, using the context-free grammar G (Definition 2) by choosing an operator σ, a threshold χ and value of discretization h. We consider that these new sets have an easy linguistic interpretability (similar to the initial
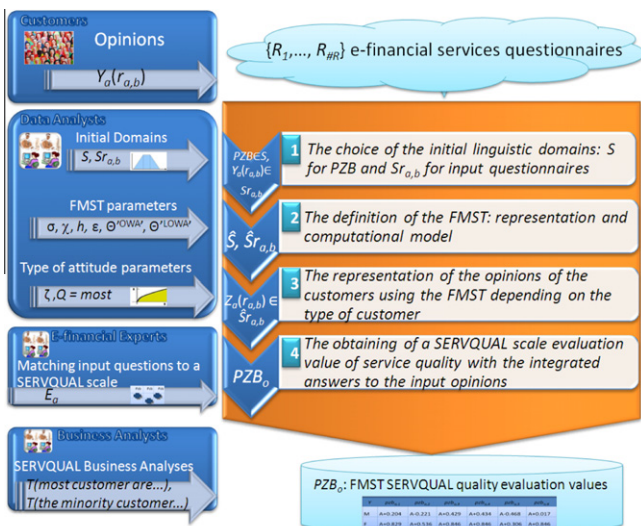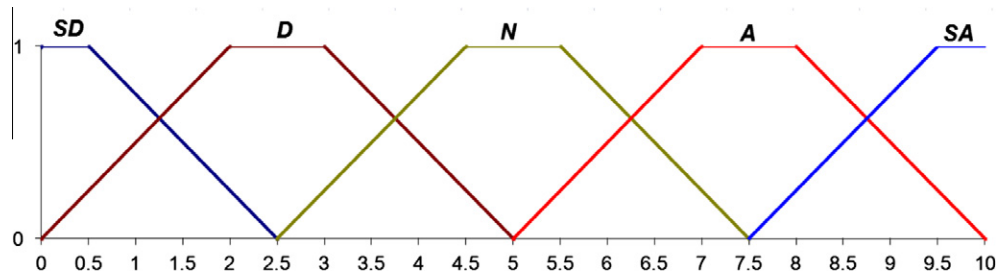
Fig. 3. Linguistic terms defined for a five-point Likert scale.
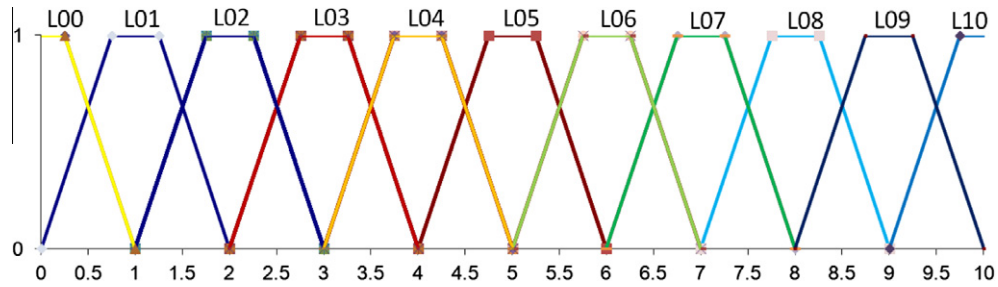

Fig. 4. Linguistic terms defined for an eleven-point Likert scale.

Table 3
Description of the questionnaire items.

Question $r_{a,b}$	Questionnaire R_a			
	R_1	R_2	R_3	R_4
Accessibility	×	×	×	×
Ease of navigation	×	×	×	×
Usefulness of the information	×	×	×	×
Simplicity of information	×	×	×	×
Customer attention	×	×	×	×
Suitability to needs	×	×	×	×
Ease of operations	×	×	×	×
Reliability of operations	×	×	×	×
Security of operations	×	×	×	×
Agility of operations	×	×	×	×
Overall satisfaction	×	×	×	×

sets) and a high precision (depending on the value h). In this way, it is possible express the initial, intermediate and end linguistic performance without losing linguistic interpretability.

- *Definition of the computational model of the FMST.* This model mainly consists of establishing appropriate operators of linguistic information necessary for linguistic summary in order to aggregate and combine the linguistic performance values provided by the customers. We define the operators $\Theta^{,\text{OWA},}$ and $\Theta^{,\text{LOWA},}$ choosing an operator ε. In this paper, we have defined these new operators (Definitions 6) based on the approximative computational model, but avoiding the major drawback of this model, i.e., the loss of precision. Therefore, we will use these enhanced operators in our model.

3.3. Representation of the opinions of customers using the FMST according to type of customer

Customers normally have different opinions such as pessimistic, optimistic and neutral attitudes because of their various experiences and individual preferences (Chin-Hung, 2008). Some authors (Huynh et al., 2006) use several linguistic terms to represent such attitudes. In this paper, we propose using the original term expressed by customers but with a negative, positive or zero semantic translation of such initial terms, respectively, for pessi-

mistic, optimistic and neutral types of customers in order to obtain a more precise representation. Obviously, a previous process is needed to obtain the type of customer. For this purpose a linguistic summary is proposed. There are two steps in this phase:

- *Identification of type of customer according to attitude.* We propose obtaining the customer's overall *pessimistic* attitude by means of a linguistic summary that may be exemplified by "T (most customer responses in the questionnaire are 'strongly disagree') $\geqslant \zeta$", where $\zeta \in [0,1]$ must be close to 1. Our proposal for *optimistic* attitudes is analogous, but using 'strongly agree' responses. Otherwise, we consider *neutral* attitudes. Therefore, for each customer of each questionnaire, i.e., $y_{a,c}$, $\forall a \in \{1,\ldots,\#R\}$, $\forall c \in \{1,\ldots,\#Y_a\}$, we calculate the linguistic summary $\mathscr{S}r_a^{Y_{a,c}} = \langle sr_a^{Y_{a,c}}, Q, Tr_a^{Y_{a,c}} \rangle$ based on the five-point Likert output questionnaire domain, S. We then we proceed to identify the type of customer according to the following procedure:

(1) *Calculation of the label $sr_{a,b}^{Y_{a,c}} \in \widehat{S}$, that best summarizes the set of all opinions provided by the customer $y_{a,c}, \{y_{a,c}(r_{a,b})\}$, according to the specified FMST (Section 3.2). Since Q = "most" is a relative quantity, we choose $W = \{w_b\}$, $w_b = 1/\#R_a$. Thus, we calculate the label that best summarizes the set as:*

$$sr_a^{Y_{a,c}} = \Theta^{,\text{LOWA},}(\widehat{S}, \{y_{a,c}(r_{a,b})\}, W), \forall b \in \{1,\ldots,\#R_a\}$$

(2) *Calculation of the value $qr_a^{Y_{a,c}}$; a relative indication of the number of pieces of data that satisfy the label $sr_a^{Y_{a,c}}$:*

$$qr_a^{Y_{a,c}} = \Theta^{,\text{OWA},}(sr_a^{Y_{a,c}}, \{y_{a,c}(r_{a,b})\}, W)$$

(3) *Calculation of the truth value $Tr_a^{Y_{a,c}}$ as the membership of $qr_a^{Y_{a,c}}$ in the proposed quantity in agreement:*

$$Tr_a^{Y_{a,c}} = Q(qr_a^{Y_{a,c}})$$

(4) *Identification of the type of customer $t_{a,c}$:*

$$t_{a,c} = \begin{cases} Pessimistic, \text{ if } sr_a^{Y_{a,c}} \in \{s_0, s_0 + \mathbf{d}^{-\prime}_{01}, \ldots, s_0 + \mathbf{d}^{-\prime}_{0h}\} \text{ and } Tr_a^{Y_{a,c}} \geqslant \zeta \\ Optimistic, \text{ if } sr_a^{Y_{a,c}} \in \{s_g - \underline{\mathbf{d}}'_{g1}, \ldots, s_g - \underline{\mathbf{d}}'_{gh}, s_g\} \text{ and } Tr_a^{Y_{a,c}} \geqslant \zeta \\ Neutral, \text{ otherwise} \end{cases}$$

- *Representation of the opinions of the customers using the FMST.* We define the new set $Z_a(r_{a,b}) = \{z_{a,c}(r_{a,b})\}$ from the set $Y_a(r_{a,b})$ with maximum, minimum or zero semantic translation of such initial terms, respectively, for pessimistic, optimistic and neutral customers. Assuming that $y_{a,c}(r_{a,b}) = s_{a,b,d}$, $d \in \{1, \ldots, \#Sr_{a,b}\}$, we define the new representation values as:

$$z_{a,c}(r_{a,b}) = \begin{cases} s_{a,b,d} + \mathbf{d}^{-\prime}_{a,b,d}, & \text{if } t_{a,c} = Pessimistic \\ s_{a,b,d} - \underline{\mathbf{d}}'_{a,b,d}, & \text{if } t_{a,c} = Optimistic \\ s_{a,b,d}, & \text{otherwise} \end{cases}$$

3.4. Obtaining a SERVQUAL scale evaluation value of service quality with the answers integrated to the input opinions

In this phase, two steps are carried out to obtain a SERVQUAL scale evaluation:

- *A process guided by the information, and provided by a set of e-financial experts.* This set is comprised of e-financial professionals who are selected for their professional knowledge and work experience, professors of business schools with research experience in this topic, and others, who are asked to associate each attribute of the input opinions to one of the n possible options ($n = 6$) of the SERVQUAL scale. After this decision process, a vector is obtained, $E_a = \{e_{a,b}\}, \forall a \in \{1, \ldots, \#R\}, \forall b \in \{1, \ldots, \#R_a\}, e_{a,b} \in \{1, \ldots, n\}$, indicating that $r_{a,b}$ is assigned to the pzb $e_{a,b}$ scale. Hence, all the questionnaires are divided into subsets, i.e., $R_a = R_{a,1} \cup \cdots \cup R_{a,n}$, with, $R_{a,i} = \{r_{a,b,i} : r_{a,b,i} = r_{a,b} \text{ if } e_{a,b} = i\}, \forall i \in \{1, \ldots, n\}$.
- *A process to obtain a SERVQUAL scale evaluation value of service quality*, PZB_o, with the integrated input opinions of the customers $\{z_{a,c}(r_{a,b,i})\}$. For this purpose, we use the linguistic summary $\mathscr{S}pzb_i^Y = \langle spzb_i^Y, Q, Tpzb_i^Y \rangle$ based on the five-point Likert output questionnaire domain, i.e., S. Therefore, we follow the following procedure to obtain each SERVQUAL scale value, $pzb_{o,i}$, $\forall i \in \{1, \ldots, n\}$:
  (1) *Calculation of the label* $spzb_i^Y \in \widehat{S}$, that best summarizes the set of all opinions provided by all customers assigned to the pzb_i scale, $\{z_{a,c}(r_{a,b,i})\}$, according to the specified FMST (Section 3.2). We choose $W = \{w_j\}, \forall j \in \{1, \ldots, \#R_{a,i}\}$ as:

$$w_j = \begin{cases} 1/\#R_{a,i}, & \text{if } Q \text{ is a relative quantity} \\ 1, & \text{if } Q \text{ is an absolute quantity} \end{cases}$$

We then calculate the label that best summarizes the set Y as:

$$pzb_{o,i} = spzb_i^Y = \Theta^{,\text{LOWA},}(\widehat{S}, \{z_{a,c}(r_{a,b,i})\}, W),$$
$$\forall a \in \{1, \ldots, \#R\}, \forall b \in \{1, \ldots, \#R_a\}, \forall c \in \{1, \ldots, \#Y_a\}$$

  (2) *Calculation of the value* $qr_a^{Ya,c}$; *a relative indication of the number of pieces of data that satisfy the label* $sr_a^{Ya,c}$:

$$qpzb_i^Y = \Theta^{,\text{OWA},}(spzb_i^Y, \{z_{a,c}(r_{a,b,i})\}, W)$$

  (3) *Calculation of the truth value* $T\,pzb_i^Y$ *as the membership of* $qpzb_i^Y$ *in the proposed quantity in agreement:*

$$Tpzb_i^Y = Q(qpzb_i^Y)$$

4. Example of an application

Several web questionnaires containing different questions and using various scales were administered at different times to survey customer satisfaction with e-financial services of a Spanish savings bank. The opinions expressed by the users of e-financial services in natural language form are an important source of information for the entity. Thus, the entity encourages users to express opinions on e-financial services through textual reviews on the e-banking website. The new model proposed in this paper was applied to integrate this heterogeneous information. The objective is to aggregate these questionnaires and textual reviews into a five-point Likert scale SERVQUAL form that characterizes according to their common features (including date of fulfillment, gender, etc.).

Let $R = \{R_1, \ldots, R_{\#R}\}, \#R = 4$ be the set of input questionnaires with the items shown in Table 3 and the following characteristics: R_1 completed during the month of August 2009, with responses on a eleven-point Likert scale (from 0 to 10); R_2 completed during September 2009, with responses on a eleven-point Likert scale (from 0 to 10); R_3 done during October 2009, with responses on a five-point Likert scale (from 1 to 5); and R_4 obtained from the online reviews of the e-banking website users. In addition, these questionnaires have some common information on customers who have responded to the questions such as gender (see Fig. 5) and age.
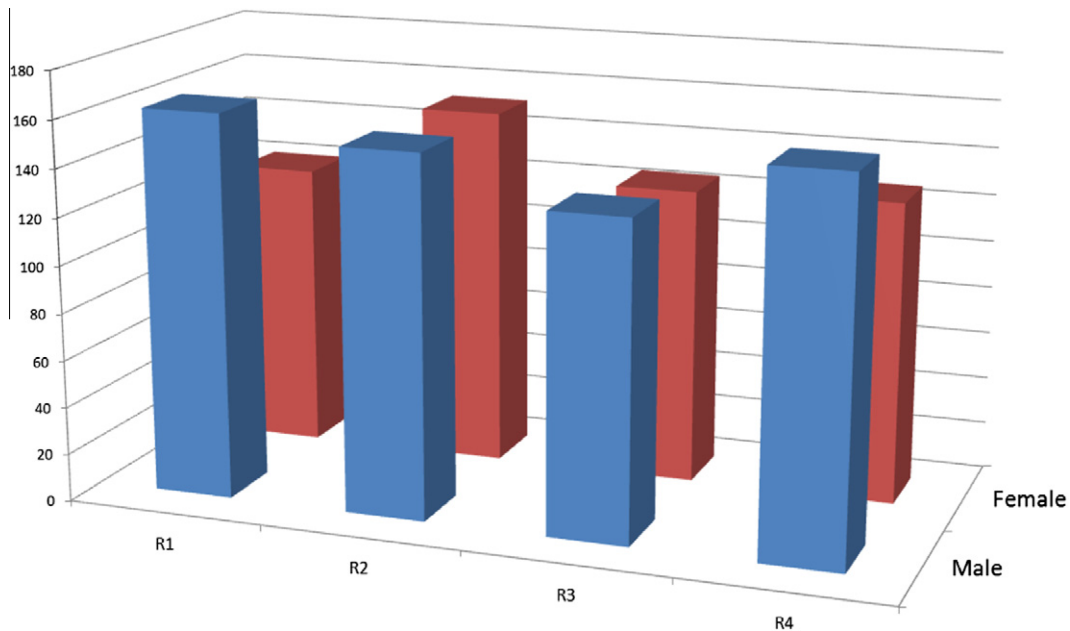

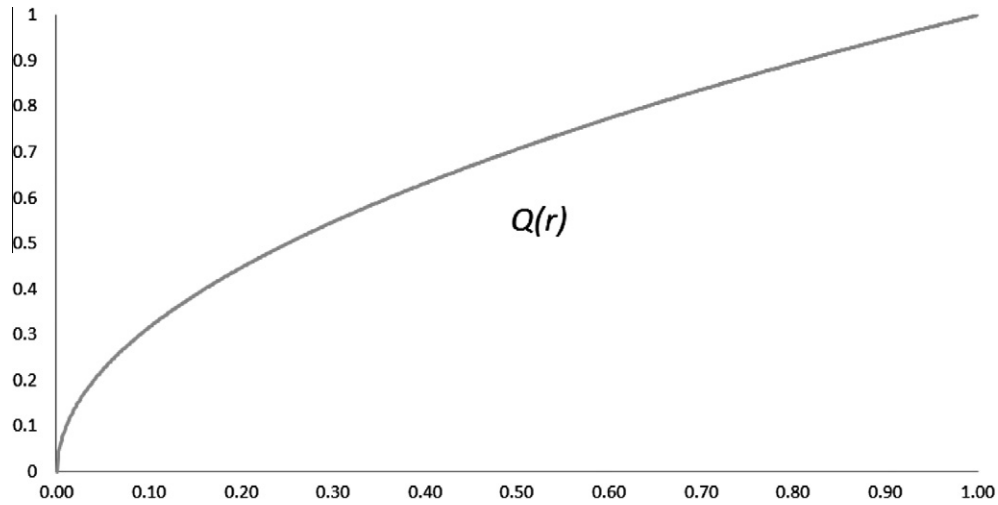**Fig. 5.** Responses to questionnaires by gender.

Fig. 6. Linguistic quantifier "most": $Q(r) = r^{1/2}$.

Table 4
Examples of identification of customer type $t_{a,c}$.

$y_{a,c}$	$sr_a^{Ya,c}$	$Tr_a^{Ya,c}$	$t_{a,c}$	$Y_a(r_{a,b})$										
				$r_{a,1}$	$r_{a,2}$	$r_{a,3}$	$r_{a,4}$	$r_{a,5}$	$r_{a,6}$	$r_{a,7}$	$r_{a,8}$	$r_{a,9}$	$r_{a,10}$	$r_{a,11}$
$y_{2,101}$	SD+0.221	0.8160	Pessimistic	L01	L00	L01	L00	L01	L01	L00	L01	L01	L00	L01
$y_{3,85}$	SD+0.166	0.7069	Pessimistic	SD	SD	SD	SD	SD	SD	SD	SD	SD	D	SD
$y_{1,1}$	SA-0.455	0.9044	Optimistic	L09	L10	L10	L10	L10	L09	L07	L10	L10	L10	L10
$y_{2,179}$	SA-0.854	0.8516	Optimistic	L10	L10	L09	L10	UNK	L10	L10	L09	L09	L10	L09
$y_{3,8}$	SA-0.748	0.7068	Optimistic	SA	SA	A	A	UNK	SA	SA	SA	SA	A	SA
$y_{3,121}$	SA-0.680	0.7068	Optimistic	SA	SA	SA	SA	SA	N	SA	SA	SA	SA	A
$y_{1,2}$	A+0.136	0.9045	Neutral	L10	L06	L08	L07	L05	L08	L08	L09	L09	L06	L08
$y_{1,52}$	N+0.638	0.9042	Neutral	L04	L00	L08	L08	L09	L05	L04	L09	L09	L00	L06
$y_{2,97}$	N-0.272	0.9204	Neutral	L10	L05	L01	L05	UNK	L01	L05	L07	L07	L05	L05
$y_{3,169}$	D+0.595	0.7315	Neutral	D	D	N	N	A	N	D	SD	SD	D	SD
$y_{4,284}$	A-0.854	0.6332	Neutral	N	A	UNK	UNK	UNK	UNK	UNK	UNK	UNK	UNK	UNK

Table 5
Examples of representations of opinions according to customer type $t_{a,c}$.

$y_{a,c}$	$t_{a,c}$	$Z_a(r_{a,b})$										
		$r_{a,1}$	$r_{a,2}$	$r_{a,3}$	$r_{a,4}$	$r_{a,5}$	$r_{a,6}$	$r_{a,7}$	$r_{a,8}$	$r_{a,9}$	$r_{a,10}$	$r_{a,11}$
$y_{2,101}$	Pessimistic	L01+0.348	L00+0.348	L01+0.348	L00+0.348	L01+0.348	L01+0.348	L00+0.348	L01+0.348	L01+0.348	L00+0.348	L01+0.348
$y_{3,85}$	Pessimistic	SD+0.846	SD+0.846	SD+0.846	SD+0.846	SD+0.846	SD+0.846	SD+0.846	SD+0.846	SD+0.846	D+0.846	SD+0.846
$y_{1,1}$	Optimistic	L09-0.352	L10-0.352	L10-0.352	L10-0.352	L10-0.352	L09-0.352	L07-0.352	L10-0.352	L10-0.352	L10-0.352	L10-0.352
$y_{2,179}$	Optimistic	L10-0.352	L10-0.352	L09-0.352	L10-0.352	UNK	L10-0.352	L10-0.352	L09-0.352	L09-0.352	L10-0.352	L09-0.352
$y_{3,8}$	Optimistic	SA-0.854	SA-0.854	A-0.854	A-0.854	UNK	SA-0.854	SA-0.854	SA-0.854	SA-0.854	A-0.854	SA-0.854
$y_{3,121}$	Optimistic	SA-0.854	SA-0.854	SA-0.854	SA-0.854	SA-0.854	N-0.854	SA-0.854	SA-0.854	SA-0.854	SA-0.854	A-0.854
$y_{1,2}$	Neutral	L10	L06	L08	L07	L05	L08	L08	L09	L09	L06	L08
$y_{1,52}$	Neutral	L04	L00	L08	L08	L09	L05	L04	L09	L09	L00	L06
$y_{2,97}$	Neutral	L10	L05	L01	L05	UNK	L01	L05	L07	L07	L05	L05
$y_{3,169}$	Neutral	D	D	N	N	A	N	D	SD	SD	D	SD
$y_{4,284}$	Neutral	N	A	UNK	UNK	UNK	UNK	UNK	UNK	UNK	UNK	UNK

As mentioned in Section 3, four steps are needed to solve this integration problem. In what follows, we explain these steps and then provide examples of analyses that a business analyst can perform using the integrated information that is obtained.

4.1. The choice of initial linguistic domains

The initial linguistic terms for all the questions of R_a, i.e., $Sr_{a,b}$, $\forall a \in \{1,2\}$, $\forall b \in \{1,\ldots,\#R_a\}$ are defined using the eleven-point Likert scale semantic shown in Fig. 4, and matching the label $L00$ with the value 0 of the responses, $L01$ with 1, etc. For the rest of the questionnaires, we choose the same five-point Likert scale initial domain, S, that we have defined for the *PZB* questionnaire (see Fig. 3), i.e., $Sr_{a,b} = S$, $\forall a \in \{3, 4\}$, $\forall b \in \{1,\ldots,\#R_a\}$. For the questionnaire R_3, we match the label SD with 0, D with 1, etc. For R_4, we use the text mining schema explained in Section 3.1 to obtain the pair of features ($r_{4,b}$) and ratings ($y_{4,c}(r_{4,b})$) to evaluate such ratings (see Table 3, e.g., ease of navigation, overall satisfaction, etc.) with the terms of the five-point Likert scale taking account the synonyms, abbreviators, etc. of such ratings and terms (e.g., "unacceptable" for SD, "poor" for D, "average" for N, "good" for A, "excellent" for SA, etc.).

Table 6
Vector E_a indicating the matching of the input questions to the *PZB* scale.

Question $r_{a,b}$	PZB scale					
	pzb_1	pzb_2	pzb_3	pzb_4	pzb_5	pzb_6
Accessibility	×					
Ease of navigation	×					
Usefulness of the information					×	
Simplicity of information	×					
Customer attention			×			
Suitability to needs					×	
Ease of operations	×					
Reliability of operations		×				
Security of operations				×		
Agility of operations	×					
Overall satisfaction						×

On the other hand, we consider that all input domains have included the value *Unknown* (*UNK*) to represent possible non-responses (defined in Section 3.1). The *UNK* values are frequent in the R_4 questionnaire since customers' textual opinions normally only contain a few items of the questionnaire.

4.2. Definition of the FMST

We proceed to define the representation and computational model for all the domains of our problem as specified in Section 3.2.

- *Definition of the computational model of the FMST.* We obtain more precise domains for the input and output questionnaires, $\hat{S}$ and $\hat{S}r_{a,b}$, by choosing the *possibly operator* shown in Table 1 for σ, the threshold $\chi = 0.7$, and the value of discretization $h = 200$, i.e., 100-lower and 100-higher semantic translations of each term of each domain.
- *Definition of the computational model of the FMST.* We define the operators $\Theta^{,OWA,}$ and $\Theta^{,LOWA,}$ by choosing the *necessity operator* defined in Table 2 for ε.

4.3. Representation of customer opinions using the FMST depending on type of customer

We follow the steps explained in Section 3.3:

- *Identification of type of customer according to attitude.* We calculate the linguistic summary $\mathscr{S}r_a^{Ya,c} = \langle sr_a^{Ya,c}, Q, Tr_a^{Ya,c} \rangle$ for each customer, $y_{a,c}$, which is guided by the fuzzy linguistic quantifier Q = "most" representing the concept of *fuzzy majority* (Kacprzyk, 1986). Yager (1996) considers the parameterized family of quantifiers $Q(r) = \rho^\kappa, \kappa = \geqslant 0$ to represent this linguistic quantifier. Therefore, we propose using the linguistic quantifier "most", which is defined as $Q(r) = r^{1/2}, r \in [0,1]$ (see Fig. 6). After

calculating $\mathscr{S}r_a^{Ya,c}$, we compute the value $t_{a,c}$ using as threshold $\zeta = 0.7$. Some examples of this identification process are shown in Table 4.

- *Representation of customer opinions using the FMST.* The two domains used in our problem, the five and eleven-point Likert scales, are defined symmetrically (see Figs. 3 and 4). Therefore, the minimum values of the semantic translation for each term are always the same within each domain. The same occurs for the maximum values. Therefore, according to the FMST parameters chosen in Section 4.2 we have: $\underline{d}'_{a,b} = 0.352$ and $\overline{d}'_{a,b} = 0.348, \forall a \in \{1,2\}$; and $\underline{d}'_{a,b} = 0.854$ and $\overline{d}'_{a,b} = 0.846, \forall a \in \{3,4\}$ (see Fig. 7 for an example). Some examples of the new set $Z_a(r_{a,b})$ obtained for the customers in Table 4 are shown in Table 5.

This model allows us to obtain a more precise representation of the opinions according to type of customer.

4.4. Obtaining a SERVQUAL scale evaluation value of service quality with the answers integrated to the input opinions

The two steps completed in the fourth phase (see Section 3.4) are described below:

- *A process guided by the information, and provided by a set of e-financial experts.* The following four experts collaborated in the process: two assistant professors from the Marketing Department of the University of Granada (Spain) with more than 10 years of experience in researching and the rating of e-services, and two bank employees belonging to the on-line banking department. The decision of the experts, i.e., the vector E_a, is shown in Table 6.
- *A process to obtain a SERVQUAL scale evaluation value of service quality.* In this process we calculate $\mathscr{S}_{pzb_i}^Y = \langle s\,pzb_i^Y, Q, T\,pzb_i^Y \rangle$ for each SERVQUAL scale in order to obtain the values of the output questionnaire, $pzb_{o,i}$. We decided to undertake this integration process according to most customers, thus we use the relative quantifier Q = "most" (defined in Fig. 6). We obtain the results shown in Table 7 by integrating all the opinions of all the customers. The table shows that all the scales have been properly evaluated with an acceptable truth value level. Note that *Responsiveness* ($pzb_{o,3}$) and *Assurance* ($pzb_{o,4}$) obtain the highest assessment, while *Empathy* ($pzb_{o,5}$), which is slightly below *Agree*, obtains the worst.

We can apply this process of integration successively at different subsets of the total customer pool. Thus, a user can analyze the temporal evolution of the SERVQUAL characteristics, that is, if these features have improved or worsened over a period of time. To do so, we consider $Y_a(r_{a,b})$ to be the set of responses in a specific month and then perform the integration process. The
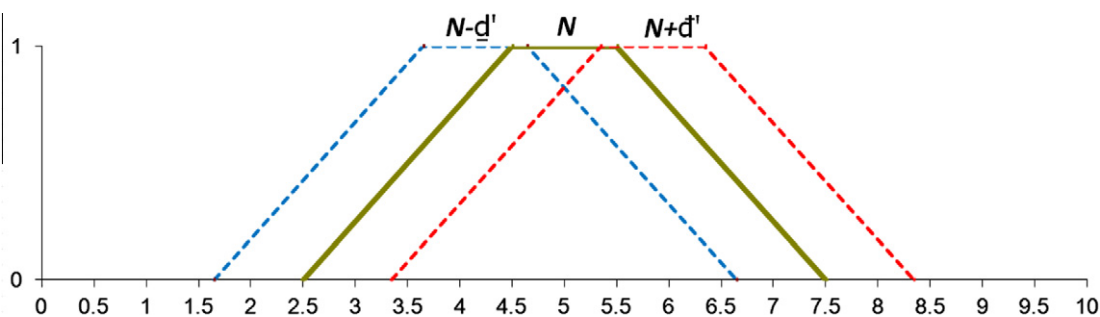

Fig. 7. Representation of the term *N* for optimistic, neutral and pessimistic customers.

Table 7
Result of the process to integrate the opinions of all customers.

$pzb_{o,1}$	$Tpzb_1$	$pzb_{o,2}$	$Tpzb_2$	$pzb_{o,3}$	$Tpzb_3$	$pzb_{o,4}$	$Tpzb_4$	$pzb_{o,5}$	$Tpzb_5$	$pzb_{o,6}$	$Tpzb_6$	$\#Y_a$
A+0.493	0.7073	A+0.132	0.708	A+0.697	0.7982	A+0.676	0.7982	A-0.123	0.7943	A+0.421	0.7983	1129

Table 8
Result of the processes to integrate customer opinions each month.

Y	$pzb_{o,1}$	$Tpzb_1$	$pzb_{o,2}$	$Tpzb_2$	$pzb_{o,3}$	$Tpzb_3$	$pzb_{o,4}$	$Tpzb_4$	$pzb_{o,5}$	$Tpzb_5$	$pzb_{o,6}$	$Tpzb_6$	$\#Y$
Ag-09	A+0.310	0.708	A+0.043	0.708	A+0.557	0.709	A+0.519	0.709	A-0.408	0.713	A+0.230	0.709	336
Se-09	A+0.591	0.707	A+0.145	0.708	A+0.714	0.852	A+0.731	0.852	A-0.021	0.850	A+0.523	0.852	391
Oc-09	A+0.553	0.707	A+0.191	0.708	A+0.803	0.835	A+0.748	0.836	A+0.030	0.829	A+0.480	0.836	402

Table 9
Result of the processes to integrate customer opinions by gender.

Y	$pzb_{o,1}$	$Tpzb_1$	$pzb_{o,2}$	$Tpzb_2$	$pzb_{o,3}$	$Tpzb_3$	$pzb_{o,4}$	$Tpzb_4$	$pzb_{o,5}$	$Tpzb_5$	$pzb_{o,6}$	$Tpzb_6$	$\#Y$
M	A+0.204	0.708	A-0.221	0.709	A+0.429	0.799	A+0.434	0.798	A-0.468	0.797	A+0.017	0.799	604
F	A+0.829	0.707	A+0.536	0.708	A+0.846	0.767	A+0.846	0.779	A+0.306	0.791	A+0.846	0.790	525

results with the three different months are shown in Table 8. As can be seem, almost all the SERVQUAL characteristics improved over time with the exception of *Tangibles* ($pzb_{o,1}$) and *OSI* ($pzb_{o,6}$), which show little change over the September–October period. It is interesting to note that the most poorly evaluated feature, i.e., *Empathy* ($pzb_{o,5}$), improved in the last month to reach a positive value of *Agree*. All these conclusions have a tolerable truth value level.

Finally, Table 9 shows the results of the two integration processes considering $Y_a(r_{a,b})$ first for men and then for women. We can conclude (with a good truth value level) that women evaluate all the features significantly better than men.

5. Conclusions and future research

Firms and financial entities are competing not only with internal and external organizations in today's global conditions. In this context, it is also important to achieve a congruent, desirable, and qualified service because quality is achieved when the desires and expectations of the consumers are met. By the relevance, the quality of the services and satisfaction should be measured (Büyüközkan & Çifçi, 2012).

In recent decades, marketing professionals have reached consensus that measuring customer satisfaction is key to developing customer-oriented strategies (Kohli & Jaworski, 1990; Narver & Slater, 1990) with a view to improving relationship marketing (Grönroos, 1996). However, there has been less agreement regarding the development of uniform methodologies and scales to measure service quality. While it is true that the SERVQUAL scale has met with greater success than other initiatives in this field, the various adaptations and changes made to the measurement scales often make it difficult to compare results over time; a key aspect that companies must take into account when implementing their market-oriented strategies. Even when the time horizons are the same, it is often impossible to aggregate the results if different types of surveys and measurement scales are used; a practice which is, at the same time, customary. Moreover, the wide range of data collection methodologies and measurement scales used by different companies in the same market prevents comparing the results of surveys to evaluate service quality.

Although it is habitual to measure human perceptions with quite accurate instruments, such perceptions are characterized by uncertainty and fuzziness. Furthermore, variations in individual percep-

tions and personality mean that the same words can indicate very different perceptions. In this context, the fuzzy linguistic approach seems to be an appropriate framework for modeling the information.

Given this heterogeneous context, we have developed a methodology for aggregating different scales to achieve greater homogeneity. This methodology can be used for making comparisons over time or between companies with a view to undertaking more precise decision making processes. Concretely, we have presented the problem of integrating semantically heterogeneous data (natural language included) from various web questionnaires with opinions about e-financial services. As a solution to this problem, we develop a model based on the fuzzy model based on semantic translation (FMST) under the perspective of the SERVQUAL instrument.

Several authors have adapted the SERVQUAL instrument to analyze e-financial services expectations and perceptions about service quality (González et al., 2008; Han & Baek, 2004), but none have adopted the fuzzy linguistic approach.

Concisely, our methodological proposal to develop a model based on the FMST under the perspective of the SERVQUAL instrument proceeds in this way:

1. We first define the initial linguistic domains for each of the questions of the input and output questionnaires in order to describe human perceptions or attitudes as linguistic performance values.
2. We then define the representation and computational model of the FMST for all the domains of our problem.
3. Customer opinions are then represented using the FMST depending on type of customer. This phase is carried out in two steps:

   - Identification of the type of customer according to attitude.
   - Representation of the opinions of the customers using the FMST.

4. The SERVQUAL scale evaluation value of service quality is obtained using the answers integrated to the input opinions. This phase is carried out in two steps:

   - The first step is led by the information provided by e-financial experts, in order to associate each attribute of the input opinions with a SERVQUAL scale of the output questionnaire type.

- The second step is guided by the information provided by the customers in order to obtain a SERVQUAL scale evaluation value of service quality with the integrated answers of the input opinions by means of linguistic summary.

The model proposed in this paper has been applied to integrate heterogeneous information drawn from four web questionnaires (from 0 to 10, from 1 to 5 and online reviews) containing various questions using several scales regarding the SERVQUAL instrument and satisfaction of customers of a Spanish savings bank.

To identify the type of customer, we calculate a linguistic summary for each customer which is guided by the quantifier "most" included in the family of quantifiers, $Q(r) = \rho^\kappa$ as proposed in Yager (1996) to verify if most customer responses are strongly disagree/agree. In this case, we consider that the customer is pessimistic/optimistic, respectively, using the threshold: $\chi = 0.7$. Otherwise, we categorize the customer as neutral. According to the FMST parameters chosen in Section 4.2, we represent customer responses by means of a maximum, minimum or zero semantic translation of the initial terms of the responses for pessimistic, optimistic and neutral customers, respectively.

Finally, future research should focus on comparing the results obtained by dividing the sample according to other variables internal to the entity such as degree of linking o dependence with the products, date of registration in the electronic services system, customer's age, or others. Moreover, it would be interesting to benchmark different entities in the sector by applying this linguistic integration process.

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