



Original Article

# Cochlear Implant Evaluation: Prognosis Estimation by Data Mining System

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**OBJECTIVE:** Prediction of speech recognition (SR) and quality of life (QoL) outcomes after cochlear implantation is one of the most important challenges for otologists. By sifting through very large amounts of data, data mining reveals trends, patterns, and relationships that might otherwise have remained undetected. There are identifiable pre-implantational factors that condition the cochlear implantation outcome. Our objective is to design a data mining system to predict and classify cochlear implant (CI) predictable benefits in terms of SR and QoL in each patient.

**MATERIALS and METHODS:** This is an observational study of CI users for at least one year. Audiological benefits and its relation to QoL are analyzed using the Glasgow Benefit Inventory (GBI) and the Specific Questionnaire (SQ). Sociodemographic and medical variables are processed in SPSS Statistics 19.0, MatLab® and Weka®. Classifiers are designed using the nearest neighbour and decision tree algorithms. Estimators are created by linear logistic regression.

**RESULTS:** A total of 29 patients (mean age, 55.3 years; 52% female and 48% male) including 48% unilateral CI users and 51% bimodal CI users were included in the study. GBI improved by 36 points and SQ by 1.7 ( $p < 0.05$ ). Using Nearest Neighbour (IB1) algorithm for classifiers, interesting attributes were identified for SR and SQ result classification (success rate: 80.7%). Decision tree algorithm (J48) showed influencing variables for GBI (success rate: 81%). Estimators by linear logistic regression analysis disclosed a precision of 85%, 68%, and 71% for SR, GBI, and SQ, respectively.

**CONCLUSION:** Our study proposes a systematized system to classify and estimate SR and QoL improvement based on our initial evaluation to complement decision making and patients' information.

**KEYWORDS:** Cochlear implants, data mining, prognosis, quality of life

## INTRODUCTION

Hearing impairment is a common chronic condition. Population-based epidemiological studies show that the prevalence of hearing impairment steadily increases with age: it affects 3% of people aged 21-34 years, 6% of people aged 35-44 years, 11% of people aged 44-54 years, 25% of people aged 55-64 years, and 43% of people aged 65-84 years<sup>[1]</sup>. The World Health Organization estimates that hearing loss affects 538 million people worldwide<sup>[2]</sup>.

It is widely accepted that a cochlear implant (CI) is the only effective treatment for profound hearing impairment and for those severe ones where conventional hearing aids are not effective. However, the preliminary prediction of cochlear implantation results in terms of speech recognition and the impact of these devices on the patients' daily life is still an important challenge for otologists.

Data mining (DM) is an interdisciplinary subfield of computer science. It is the computational process of discovering patterns in large data sets involving methods at the intersection of artificial intelligence, machine learning, statistics, and database systems. The overall goal of the DM process is to extract information from a data set and transform it into an understandable structure for further use. Such information may include data classification and prediction of outcomes after an intervention, or it may study the association, group, or detection of variable deviation<sup>[3]</sup>.

Data mining involves the following six common types of tasks: anomaly detection, association rule learning, clustering (the task of discovering groups and structures in the data that are in some way or another "similar" without using known structures in the data), classification, regression (which attempts to find a function that models the data with minimum error), and summarization (which provides a more compact representation of the data set including visualization and report generation).

There are recognizable factors that determine cochlear implantation results before implantation, such as profound hearing loss duration<sup>[4]</sup>, age at implantation<sup>[5-8]</sup>, amount of residual hearing, support from family, demographic factors, and educational factors<sup>[9]</sup>.

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It is plausible to assume that the preliminary analysis of multiple factors related to the patient allows us to predict, in the first evaluation, cochlear implantation benefits.

The objective of this project is to design a DM-based system to classify and estimate CI results in terms of speech recognition (SR) and quality of life (QoL) in adult patients with severe to profound sensorineural hearing loss. Therefore, our aim is to determine which variables condition these results and to create an objective classification of patients into prognosis groups according to their initial evaluation.

## MATERIALS and METHODS

Conducted according to the principles expressed in the Declaration of Helsinki, this study has been approved by our Hospital Ethics Committee. The purpose and procedure of the study were orally presented by the experimenter. The experimenter then answered any questions the subject had regarding his/her participation. Finally, each subject read and signed an Institute Review Board approved informed consent form.

### Subjects

The studied group included all unilateral cochlear implanted patients within our region between February 2007 and October 2012. Inclusion criteria were for the patient to be over 18 years, to have suffered from severe to profound hearing impairment, to have undergone unilateral cochlear implantation, and to be a CI user for at least 1 year. Bilateral CI patients, reimplanted patients, and patients with unilateral hearing impairment with or without invalidating tinnitus were excluded.

### Design

We carried out an observational retrospective study at our Department of Hearing Loss.

### Instrumentation

Sociodemographic and medical variables such as etiology and length of deafness, preoperative auditory threshold, tinnitus at any point were collected. The previous use of hearing aids, model, length of use, and CI codification strategies were also reviewed. Major and minor complications were studied.

Preoperative and postoperative pure tone audiograms and an SR test (developed by Cárdenes and Marrero using vocal and consonant phonemes, disyllabic words, and sentences) were collected.

A pure tone average threshold was obtained from each patient for the audiometric threshold in conversational frequencies (500, 1000, 2000, and 4000 Hz).

To quantify improvements in QoL, the following two questionnaires were completed by patients during a personal interview at the time of the study: a Specific Questionnaire (SQ) (developed by Faber et al. in 2000)<sup>[10]</sup> and the Glasgow Benefit Inventory (GBI) (developed and validated by Robinson et al. in 1996)<sup>[11]</sup>.

Specific Questionnaire: SQ evaluates the following six different aspects related to cochlear implants: SR (3 items), social interaction (1 item), telephone use (3 items), confidence (1 item), family life (1 item), and

satisfaction (5 items). These nine items were evaluated twice, asking the patient to rate both the preoperative and the present situation on a numeric scale from 1 to 5. A statistical comparison between both ratings provides information about changes in each item.

Global Benefit Inventory: GBI is a measure of patient benefit developed particularly for otorhinolaryngological (ORL) interventions<sup>[11]</sup>. Patient benefit is the change in health status resulting from health care intervention. GBI is an 18-item post-intervention questionnaire developed to be patient-oriented and maximally sensitive to ORL interventions and to provide a common yardstick to compare benefits across different interventions. Each answer is based on a scale of 5 levels from a "big change for the better situation" to a "big change for the worse situation;" thus, the patient evaluates if an improvement has taken place and no statistical analysis is necessary. The final score is obtained by subtracting 3 from the mean value of the 18 items and multiplying it by 50. It is translated to a benefit score between -100 (maximum negative benefit) and +100 (maximum positive benefit) where 0 means no change. This questionnaire can be divided in three subscales as follows: general health (items 1, 2, 3, 4, 5, 6, 9, 10, 14, 16, 17, and 18), social interaction (items 7, 11, and 15), and physical or somatic state (items 8, 12, and 13).

Patient interviews were performed regarding the mode and communicative level of the subjects involved in the study. Likewise, the frame and mode of development of the project allowed an exchange with the studied population, giving us the opportunity to know and understand the characteristics and incidence of hearing impairment in the dynamics of communication, raising awareness of the benefits to QoL they get from assistive listening devices and providing strategies for better use.

### Statistical Analysis

Data were collected and statistically processed using Statistical Package for the Social Sciences 19.0® for Windows (IBM SPSS Statistics; Armonk, NY, USA). A descriptive analysis of the results was made by checking the users' degree of satisfaction and audiological objective results. Moreover, a correlation is sought in the outcome of health-related QoL with the audiometric performance of audiological tests. SQ results were analyzed using the Wilcoxon Test for paired samples. No analysis is needed for GBI rates. GBI and SQ scores were studied to seek a correlation for various parameters related to CI use (age at the moment of implantation, length of hearing loss, months wearing the processor, and demographic data) for which contingency tables, rather than parametric tests, were used depending on the variables. The statistical significance level was established at a p value of <0.05.

Further, a database was created in MatLab® and processed in Weka®, which helped identify those variables that significantly influence the CI outcome in terms of QoL and SR.

An automatic selection of attributes was made to optimize variables under analysis. This technique selects those variables that have a higher quantity of information for a specific classifier or estimator and deletes those that reduce the accuracy of classifiers and estimators because they are related to other variables or bring duplicated information.

Classifiers were created through the K-nearest neighbor algorithm (KNN), using the IBK system, and J48 decision tree. These classifiers, depending on CI variables or attributes before implantation, indicate what kind of results will reach the patient (good, neutral, or bad) after implantation. To design these classifiers, outcome variables (GBI, SQ, and SR) were designated as described in table 1. KNN is a memory-based algorithm, whose background idea is based on the fact that past experiences can help us solve current ones by analogy. It considers each example as a vector of  $n$  components, where  $n$  is the number of attributes or features. It does not need a learning stage. To predict the type of an unlabeled example, the algorithm compares the input example with every example in the training data, or memory, by calculating the distance between them. Then, the majority type among the  $K$  examples that are more similar to the training examples is the type predicted for the input example. In the case of J48, the model is a tree where each node corresponds to an attribute or variable and each arc of the node corresponds to a possible value of the node attribute; thus, this model classifies each case based on different attributes.<sup>[12]</sup> Accuracy of classifiers is defined by its success rate, or percentage of success, which is the fraction, or percentage, of correct results achieved among a number of attempts; thus, classifiers are better and more precise as their success rates are closer to 1 (100%).

Regression has been used to create estimators. It attempts to find a function that models the data with minimum error. Classifiers and estimators are cross-validated by evaluating the results of a statistical analysis and ensuring that these classifiers and estimators are independent to the partition between training and test data sets.

## RESULTS

Twenty-nine patients (15 males and 14 females) were included in the study. The average age at cochlear implantation was  $55.3 \pm 14$  years old. 52% of patients were implanted with a Nucleus Freedom® CI24RE model (Cochlear; Basilea, Switzerland), 24% with a Nucleus® 5 CI512 (Cochlear; Basilea, Switzerland), 21% of patients were implanted with a SONATA® TI<sup>100</sup> (MeDel, Durham, UK), and 3% of patients were implanted an Advanced Bionics® AB (Advanced Bionics, Stäfa, Switzerland) model. The number of years wearing the processor at the time of the study was  $3.1 \pm 1.6$  years.

### Audiometric Evaluation

The average length of severe to profound deafness before cochlear implantation was  $26 \pm 16.5$  years. At the moment of the study, 14 patients (48.2%) were unilateral CI users and 15 patients (51.7%) used a CI and a hearing aid in the non-implanted ear (bimodals).

The studied group had an average audiometric threshold of  $103 \pm 14$  dB before implantation and  $40.75 \pm 14.5$  dB after implantation. Word recognition was  $9.6 \pm 17.6\%$  before CI and  $58.2 \pm 28.7\%$  after CI, which means a significant benefit of  $49 \pm 32\%$  ( $p=0.001$ ). Benefits in word recognition was statistically higher in men (average benefit of  $58 \pm 33\%$ ) than in women (average benefit of  $38 \pm 30\%$ ) ( $p=0.033$ ). Regarding age, there is a weak negative association between age at cochlear implantation and word recognition (RR -0.101,  $p=0.6$ -Pearson-; RL 0.6). Older patients obtained poorer results in terms of SR. Time of hearing impairment before cochlear implantation was inversely and weakly related to profit in word recognition (RR -0.2,  $p=0.08$ ). A lon-

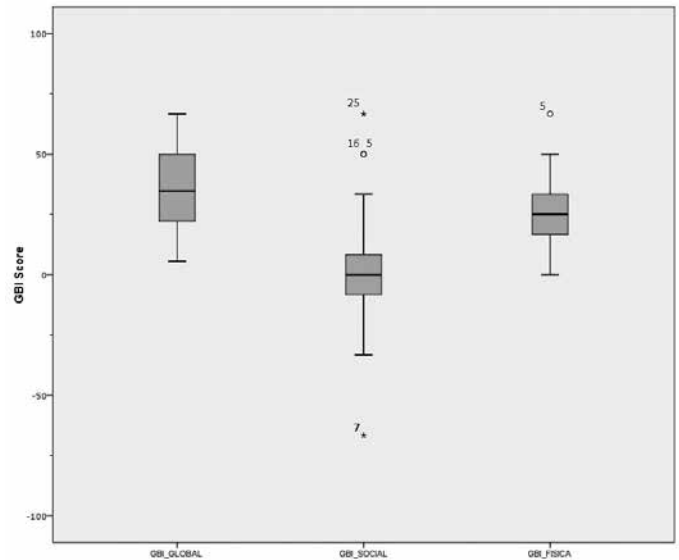


Figure 1. Graphic representation of GBI global rate and its subscales

ger evolution of hearing impairment seems to be related to poorer benefits for speech perception.

No significant differences in speech perception related to education level, employment situation, marital status, or family history of hearing loss were found in our sample. There were no differences according to the etiology of hearing loss, age, manner for establishing hypoacusis, associated systemic diseases or tinnitus suffering, previous use of hearing aids, daily use of processor, or years after CI.

### Quality of Life Evaluation: GBI and SQ

The GBI global rate and its subscales are represented in figure 1. Global GBI obtains a score of  $36 \pm 17.8$ ; Social subscale,  $2.4 \pm 25.4$ ; Physical subscale,  $26.8 \pm 13.6$ .

Specific Questionnaire mean value was  $1.2 \pm 0.9$  before implantation and  $2.9 \pm 0.8$  after implantation. This represents a statistically significant improvement in QoL ( $p=0.05$ ), with a mean benefit of  $1.7 \pm 1$ .

Statistical correlation between GBI and SQ results and age was observed ( $p=0.001$  and  $0.0001$ , respectively); older patients at implantation experienced a higher subjective satisfaction after cochlear implantation regardless of their CI audiometric benefit.

No significant differences were found in our sample related to education level, employment situation, marital status, or family history of hearing loss. Regarding aural history, no differences were found according to the etiology of hearing loss, age at hearing impairment, length of deafness, systemic associated diseases or tinnitus suffering, previous use of hearing aids, daily use of processor, or years after CI.

### Data Mining Analysis

Classifiers were created through KNN and the J48 decision tree. Based on preimplantation attributes, classifiers will indicate what kind of result will be obtained after CI (bad, neutral, or good). Outcome variables (GBI, SQ, and SR) were designated as a bad, neutral, or good result as described in Table 1.

## Classifiers

Taking into account the best algorithms (table 2), the interesting attributes for SR in words are category (unilateral cochlear implant vs bimodal), SR in a noisy environment, and being able to phone before CI. Parameters "Voice identification in noisy environment" and "being able to use the phone before CI" belong to SQ. In table 3, the success rate of each algorithm applied for each outcome variable is shown. Thus, the best system for predicting SR is IB1-KNN, with a success rate of 80.7%. Figure 2 shows the KNN graphical representation; circles and quadrangles represent "neutral" and "good" results, respectively.

**Table 1.** Outcome variables (GBI, SQ, and SR) were divided into three groups as follows: good, neutral, or bad. Limit values are described

	GBI (-100 to +100)	SQ post CI (0-4 points)	Speech perception (0-100%)
Bad	<25	<1	<60
Neutral	25-50	1-3	60-80
Good	>50	>3	>80

GBI: Glasgow Benefit Inventory; SQ: specific questionnaire; CI: cochlear implant

**Table 2.** SR of each algorithm for each outcome variable

	SQ	GBI	Speech perception
IB1	80.77	76.92	80.77
IB2	76.92	73.08	76.92
IB3	76.92	69.23	76.92
IB4	73.08	69.23	65.38
IB5	69.23	65.38	69.23
J48	76.92	80.77	76.92

GBI: Glasgow Benefit Inventory; SQ: specific questionnaire; IB 1, 2, 3, 4, and 5: nearest neighbour algorithms, types 1, 2, 3, 4, and 5; J48: decision tree type J48

**Table 3.** Interesting attributes to estimate the value of each outcome variable

Speech recognition	GBI	SQ
• Sex	• Sex	• Marital status
• Education level	• Age at implantation	• Etiology
• Labor situation	• Category	• Beginning age of hearing impairment
• Familiar antecedents	• Education level	• Comorbidities
• Etiology	• Labor situation	• Tinnitus suffering
• Beginning age of hearing impairment	• Marital status	• Previous use of hearing aids
• Length of deafness	• Coexistence situation	• Audiometric threshold
• Systemic diseases	• Beginning age of hearing impairment Hearing impairment duration	• SR of words
• Tinnitus	• Comorbidities	• SQ after CI except 4.1
• Previous use of hearing aids	• Tinnitus	
• Audiometric threshold	• Previous use of hearing aids Audiometric threshold	
• SR of sentences	• SR (words and sentences)	
• SQ before CI	• SQ after CI except 4.1 (self-confidence related)	
• Living situation		
• Familiar antecedents		

GBI: Glasgow Benefit Inventory; SQ: specific questionnaire; CI: cochlear implant; SR: speech recognition

Regarding GBI, the influencing variables are the marital status and living situation, age at the beginning of hypoacusis, and the previous use of hearing aids. Having tried all the algorithms, it is concluded that the best system to predict QoL, evaluated by GBI, was a J48 decision tree with a success rate of 80.7% (Table 2).

The most interesting attributes for SQ were the education level, SR over the phone and CEPA index before cochlear implantation. Success rates are represented in table 3; the best system to predict QoL, evaluated by SQ, was IB1-KNN with a success rate of 80.7%.

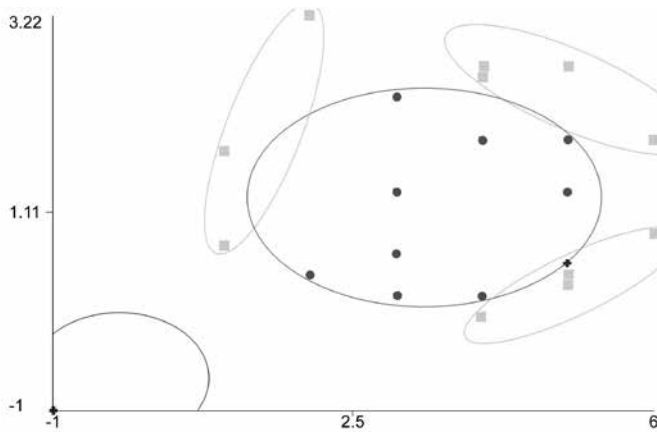
## Estimators

Regression has been used to create estimators. Linear regression obtained a success rate of 85% for word recognition, 68.4% for GBI, and 71.2% for SQ. Figures 3, 4, and 5 represent linear regression results for word recognition, GBI, and SQ, respectively. The prediction of the estimator is calculated by the distance to the real value in each case. Selecting the best algorithms, the interesting attributes to estimate, and the value of each outcome variable are detailed in Table 3.

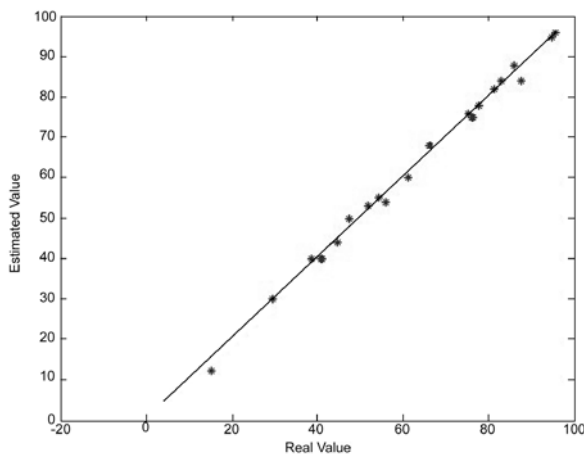
## DISCUSSION

The overall goal of the DM process is to extract information from a data set and transform it into an understandable structure for further use. Aside from the raw analysis step, it involves database and data management aspects, data pre-processing, model and inference considerations, interestingness metrics, complexity considerations, post-processing of discovered structures, visualization, and online updating.

The actual DM task is the automatic or semi-automatic analysis of large quantities of data to extract previously unknown interesting patterns such as groups of data records (cluster analysis)<sup>[13]</sup>, unusual records or anomaly detection<sup>[14]</sup>, and dependencies or association rule mining. These patterns can then be seen as a kind of summary of



**Figure 2.** Graphic representation of KNN; circles and squares represent “regular” and “good” results, respectively

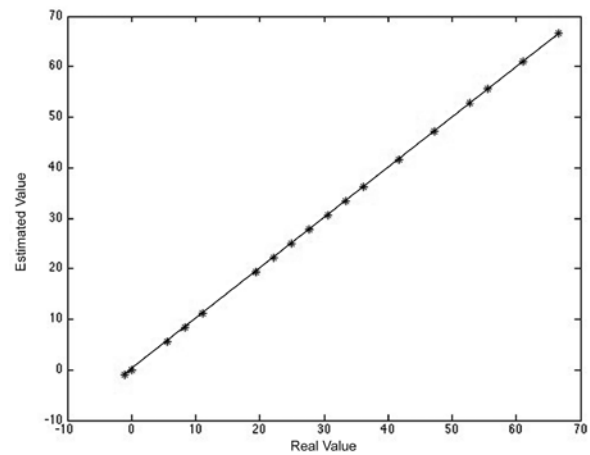


**Figure 3.** Representation of word recognition estimation by linear regression

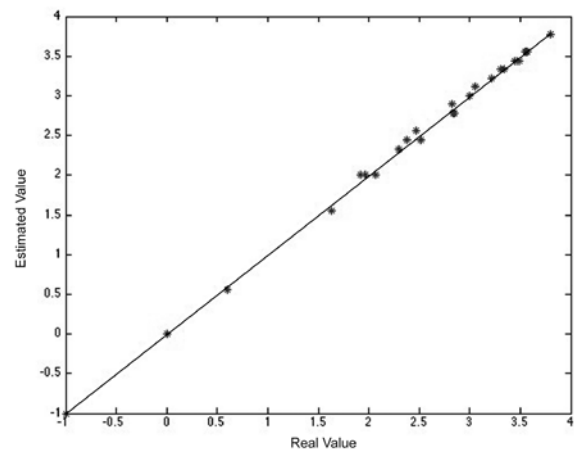
the input data, and may be used in further analysis in machine learning and predictive analytics. For example, the DM step might identify multiple groups in the data that can then be used to obtain more accurate prediction results by a decision support system.

Data mining has been applied in different fields. In business <sup>[15]</sup>, for performing market analysis to identify new product bundles, finding the root cause of manufacturing problems, to prevent customer attrition and acquire new customers, cross-sell to existing customers, to profile customers with more accuracy, and detect customer churn <sup>[16, 17]</sup>. Data clustering can also be used to automatically discover the segments or groups within a customer data set. DM has been also helpful to human resources departments for identifying the characteristics of their most successful employees. Information obtained (such as universities attended by highly successful employees) can help human resources focus on recruiting efforts accordingly.

Data mining has been widely used in medical fields with the ability of obtaining information from large data sets that contribute to decision making and problem solving. Classification has been one of the most important tasks in this field, where the model can be used for the diagnosis of many diseases. It has been applied by the Food and Drug Administration (FDA) for quantitative detection of adverse effects associated to drugs <sup>[18]</sup> and even as a predictor of stroke risk <sup>[19]</sup>.



**Figure 4.** Representation of GBI estimation by linear regression



**Figure 5.** Representation of SQ estimation by linear regression

Specifically in otoneurology, DM-based techniques have been especially designed to predict and classify the level of hearing loss in children <sup>[20]</sup>, to classify patients with Meniere’s disease in prognosis groups <sup>[21]</sup> or to predict its evolution <sup>[22]</sup>.

The present study shows the important benefits of Cis in noise perception, SR and QoL. Word recognition obtained in our sample a significant benefit of  $49 \pm 32\%$  ( $p=0.001$ ). Benefits in word recognition was statistically higher in men (58%) than in women (38%), probably because a different, but not significant, distribution in categories in our sample size with a higher proportion of bimodals among women (57%) compared with its proportion among men (46%) ( $p>0.05$ ). On the other hand, previous studies have proved that sex may have an influence on the hearing performance of postlingually deafened adults with CI <sup>[23, 24]</sup>.

Accordingly to previous studies <sup>[6, 8]</sup>, older patients obtained poorer results in terms of SR. Significant changes in QoL have been demonstrated in our sample according to GBI (Table 2, Figure 1) and SQ. Figure 1 shows the GBI global rate, social rate, and physical rate with average values of 36, 2.4, and 26.8 respectively. SQ had an improvement of 1.7 over 4. Older patients experienced a higher subjective satisfaction after cochlear implantation, regardless of their CI audiometric benefit. Similar and consistent results had been previously observed by different studies in the past <sup>[8, 25-28]</sup>.



Numerous large scale studies have demonstrated that several previous patient attributes condition cochlear implantation outcomes. In fact, our linear regression reassert that age, time of hearing impairment, previous use of a hearing aid <sup>[4-8]</sup>, and substantial preoperative residual hearing improves CI benefits <sup>[29]</sup>.

The primary cause of deafness also has a considerable impact on outcomes of cochlear implantation and rehabilitation <sup>[9]</sup>. A clear example of this is hereditary deafness due to connexin mutations <sup>[30]</sup> or to ototoxic drugs versus sudden sensorineural hearing loss <sup>[31]</sup>. The importance of etiology was also shown in our sample size, this being important for our SR and SQ result predictions (Table 3).

Psychological attributes have been related to deafness, finding elevations in depression, social introversion, suspiciousness, social anxiety, and loneliness. Studies suggest continued psychological benefits for people receiving CIs. Across the time of study, candidates showed an increase in expectations for implant success that could influence subjective satisfaction. Cohabitation situations have been associated with CI results, showing that spouses experience elevated levels of psychological distress, with a paradoxical interaction found between marital status and deafness <sup>[32, 33]</sup>. Given the evidence that the effects of general health perceptions and mental functioning on generic QoL are substantial, deaf people perceive their health status as an important component of deaf-specific QoL. Similarly to the general population, deaf people who report positive QoL are likely to perceive their health to be good. Self-acceptance of hearing loss is also an important part of the person's health status and QoL. Regardless of whether the patient is a student in college or a working adult, the necessity of being recognized and accepted as a deaf member in their environment is consistent; acceptance by peers, colleagues, and/or professors or supervisors within their primary environment has a profound impact on having their accessibility needs being met, which then allows them to fully participate in daily activities <sup>[34]</sup>. DM analysis in our sample also indicates the importance of several sociodemographic factors such as education level, labor situation, marital status, and living situation (Table 3).

Despite CI fitting and specific software tools that also influence CI outcomes <sup>[35]</sup>, no differences have been found in our sample by the DM system.

Despite this knowledge, no systematized system exists in audiology that allows an objective and numeric prediction of CI results. It is pre-operatively and objectively estimated by words recognition percentage and QoL changes. Through the proposed system, otologists can classify and estimate SR and QoL results after CI with just an initial evaluation consisting of a clinical and demographic history, a complete audiometric evaluation, and filling in a questionnaire. Figures 3, 4, and 5 represent linear regression results for expected and real values for word recognition, GBI, and SQ respectively. As shown, this system provides high accuracy with estimated values being very similar to real values. Figure 2 displays a graphic representation of the SR results, being the crucial attributes to classify outcomes in our sample category (unilateral cochlear implant vs bimodal), SR in a noisy environment, and the ability to use a phone before CI.

Thanks to this system, physicians have complementary information to improve the accuracy of the expected results from cochlear im-

plantation in each case. This system sustains and complements us in decision making and providing patients with good information.

The attributes obtained depend on the training data provided to the algorithm. Therefore, a better and more reliable model could be obtained if more quality data is provided for training.

This study gave promising and valuable contributions to the medical management and decision making process, particularly in the profile of CIs. It has proposed an innovative system based on DM techniques to objectively estimate CI results in terms of QoL and speech perception. The attributes obtained depend on the training data provided to the algorithm. Therefore, a better and more reliable model could be obtained if more quality data is provided for training.

**Ethics Committee Approval:** Ethics committee approval was received for this study from the ethics committee of our center, Complejo Hospitalario Insular Materno Infantil.

**Informed Consent:** Written informed consent was obtained from patients who participated in this study.

**Peer-review:** Externally peer-reviewed.

**Author Contributions:** Concept - A.R.D.M.; Design - A.R.D.M., G.G.J., J.C.F.G.; Supervision - A.R.M.; Resources - A.R.M., S.B.B.; Materials - D.P.P., S.B.B.; Data Collection - G.G.J.; Data Processing - A.R.D.M.; Analysis and/or Interpretation - A.R.D.M., J.C.F.G.; Literature Search - G.G.J.; Writing Manuscript - G.G.J.; Critical Review - D.P.P., A.R.M.

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