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Article

Comparison of Medical Opinions About the Decrease in Autopsies in Mexican Hospitals Using Data Mining

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Abstract: Subgroup discovery (SD) is a data mining technique that allows us to obtain the properties of each element given a particular population; these properties are of interest for a specific study, finding the most important or significant subgroups of the population. Also, the larger the population, the more successful the analysis and the creation of the subgroups, since, on this basis, the possibility of finding more unusual characteristics among the elements of the population is greater. The principal purpose of SD is not to obtain a predictive function, but to achieve a result that users can comprehend and interpret easily, and at the same time provide a more complete and suggestive description of the data. In this paper, we present an application of this technique to the medical field to analyze the opinions of physicians on the decreasing rates of autopsies in Mexican hospitals, utilizing five SD algorithms. The results obtained are the rules that allow for the comparison of medical opinions in three hospitals.

Keywords: autopsy; data mining; subgroup discovery

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1. Introduction

The number of autopsies performed in Mexican hospitals and in several countries (e.g., Netherlands [1,2], Korea [3], and Iceland [4]) has decreased considerably since the last decades of the 20th century [5]. This problem has raised research efforts to increase these studies since they remain indispensable to make correct diagnoses [6–8].

There are two kinds of autopsies: medical or non-legal (clinical or hospital) and legal (coroner, forensic, or medicolegal). In this work, data from medical and non-legal autopsies are considered. The integral part of medical autopsies is to recognize the main disease or diseases that cause death or induce the death of a human being, although they are also applicable in veterinary medicine [9,10].

A clinical autopsy is a procedure that aims to study the main disease causing death, the organs affected by the disease, and the anatomo-clinical correlation, and, in turn, to achieve the continuous quality improvement of medical work despite its worldwide decline. The practice of such a procedure contributes significantly to the medical knowledge and learning of physicians in training [11]. Consequently, the pathology area of the Hospital Regional Río Blanco (H.R.R.B.) surveyed its medical staff to find out the reasons, motives, and circumstances of this decrease.

The results were already known in our previous work [12], where a system to analyze the results of the surveys applied at H.R.R.B. was developed using descriptive (association rules) and predictive (classification) data mining tasks. Subsequently, Emergent Pattern Mining (EPM) was applied to analyze the medical opinions [13,14]. EPM is a technique belonging to Supervised Descriptive Rule Discovery (SDRD), to which Subgroup Discovery and Contrast Pattern Mining (CSM) also correspond. This work aims to compare the medical opinions of the H.R.R.B. with those of two new hospitals: the Hospital General de Zona 53 of the State of Mexico (H.G.Z.53) and the Hospital General San Juan Bautista Tuxtepec of the State of Oaxaca (H.G.S.B.T.). For this purpose, the data sets obtained from the three hospitals were analyzed using five SD algorithms (SDBeamSearchDisjunctive, SDMap, BSD, BeamSearch, and SimpleDFS), which, subsequently, with the help of the developed system, support the obtaining of rules with significant value for the specialist physicians.

The novelty of this paper is twofold: first, our main contribution is a Subgroup Discovery (SD) module to compare medical opinions about the decreasing rates of autopsies in hospitals. SD is a data mining technique that facilitates obtaining interesting patterns concerning the class label attribute. These patterns are relevant to a given study, allowing for the identification of the most significant subgroups within the population. Second, we provide a tool to pathologists that facilitates the visual analysis of the subgroups.

Sections 2–5 structure the remainder of this paper. Section 2 includes related work; Section 3 describes the methodology, some fundamental definitions, and an analysis of the data sets using SD algorithms. Section 4 contains the experimental findings. Section 5 presents the new SD module. Section 6 shows the discussions and results. Finally, Section 7 presents conclusions and future work.

2. Related Works

This section first presents two previous works and then describes some approaches related to this research considering four criteria: (1) if they perform the comparison of opinions, (2) if they use some visualization technique to facilitate comparison, (3) if they apply SD, and (4) if they focus on the medical area.

The main contribution of Rubio Delgado et al. [12] was their comparative analysis of classification and association algorithms to select the one that was optimal for their implementation in the system to analyze surveys on the decrease in autopsies in the H.R.R.B. They obtained data mining models, applying algorithms provided by the WEKA application programming interface such as J48, NaiveBayes, MultiLayerPerceptron, BayesNet, FPGrowth, PredictiveApriori, and Tertius. MultiLayerPerceptron, with the attribute selection measure InfoGain, was the best classification algorithm, and most of the rules obtained using the Tertius algorithm were approved by the expert. Subsequently, Ríos-Méndez et al. [13] applied EPM to find discriminative characteristics with respect to aspects associated with, for instance, the training and experience of physicians in relation to the motives contemplated by the doctors for requesting or rejecting autopsies. Subsequently, in [14], four attribute class labels were contemplated corresponding to the reasons why the family of the deceased refused an autopsy, the reasons why autopsies are not performed in the hospital, the convenience of the staff to request an autopsy, and the physician's reasons for requesting an autopsy.

On the other hand, CS mining and clustering algorithms, such as K-means, were implemented in López-Martinez et al. [15], where they proposed trace-based clustering to help physicians identify patients' phenotypes. Another similar work is that of Jahan et al. [16], where they determined influential risk factors for different types of cancer using association rules and contrast sets. Similarly, Varlamis [17] applied the Python implementation of the STUCCO (Search and Testing for Understandable Consistent Contrasts) CS mining algorithm in drug prescription data and diagnostics to detect medication-related risk factors linked to the prognosis of comorbidity. Al-Taie et al. [18] presented the PSDR (Patient Stratification and Drug Repositioning) framework containing three modules: (1) data and material processing, (2) subpopulation discovery, and (3) evaluation of candidate drugs. Cañete-Sifuentes et al. [19] defined the concept of contrast multivariate patterns and proposed the MHRFm (Multivariate Hellinger Random Forest miner) algorithm to extract them. In [20], contrast patterns were used to provide more information to support customers' purchasing decisions using customer support hotspots that occur frequently in reviews through DCFS (Distinguishing Customer Focus Sets).

Regarding DS, Al-Taie et al. [21] focused on finding subgroups of breast cancer patients who share common genetic profiles and identified medicines with high potential for each group. They used a data set of 980 breast cancer patients acquired from TCGA (The Cancer Genome Atlas) and performed a differential analysis between 94 normal and 980 tumor samples. Their method consisted of two parts: (1) identification of homogeneous subgroups through the mining of genotypic patterns, and (2) finding adequate medications for each group by developing and applying a medicine repositioning algorithm that uses graph analysis. For their part, Mattos et al. [22] proposed the ESM-AM (Exceptional Survival Model Ant Miner) algorithm to discover subgroups of patients with atypical survival behavior during the treatment of a disease. ESM-AM uses ACO (Ant Colony Optimization) as a search strategy for the rule induction process. Fourteen data sets were used to evaluate ESM-AM, and it was demonstrated that it obtained compact models and homogeneous subgroups.

In contrast, Liu et al. [23] used both SD and CS, since they presented a unique exploratory mining approach that allows for the biomedical research community to identify subgroups of patients who could benefit from surgeries that are probable to be effective for the target populations. The process consisted of three components: (1) a module with an algorithmic approach that executes a selection process with a succession of inclusion and exclusion processes to evaluate contrasts between cohorts, (2) contrast pattern mining, and (3) prioritization of subgroups. Autism research data sets were used to evaluate this method for cohort discovery, and it was shown that novel genes for the autism research community were discovered.

Another work related to the analysis of surveys about autopsy decreasing rates is [24], which described the results of a survey that examined physicians' attitudes toward autopsy reports and found that all categories of physicians in all clinical departments value autopsy reports as essential to improving clinical practice and patient care. According to the survey results, all physicians were found to value autopsy reports and considered them essential for improving clinical practice and patient care. However, there are still many barriers to adequate provision and utilization of the autopsy service, including cultural barriers, religious barriers, and problems in the follow-up process.

Likewise, Olowookere et al. [25] emphasized the need to improved attitudes and practices related to autopsies to optimize medical care and training. This study highlights the marked decline in the performance of autopsies in the medical field worldwide, analyzing the factors contributing to this trend due to over-reliance on modern diagnostic technologies.

A similar study is [26], where Cauteruccio and Terracina proposed an approach for extended high-utility pattern mining using Constraint Logic Programming (CSP). The paper includes a detailed discussion of the proposed approach, its implementation in Answer Set Programming (ASP), and experiments to evaluate the effectiveness of the approach in terms of performance and quality of results. A potential application of the approach in a biomedical context, specifically in predicting Intensive Care Unit (ICU) admission of COVID-19 patients, is also presented. The authors conducted experiments using a real data set of COVID-19 patients including blood test results and patient vital signs, and the results also demonstrate that the proposed approach outperforms other high-utility pattern mining approaches in terms of efficiency and effectiveness.

Most previous articles were selected as a result of a comparative analysis of 39 papers related to the application of SD and CSM methods, presented in [27], where no proposal was found that applies the following four criteria: (1) comparison of opinions, (2) visualization, (3) application of SD, and (4) focus on the medical area. Table 1 compares the related works considering these criteria.

Table 1. Comparison of the related studies.

Article	Comparison of Opinions	Use of Visualization	Subgroup Discovery	Focus on the Medical Area
Rubio-Delgado et al. [12]	No	No	No	Yes
Ríos-Méndez et al. [13]	Yes	No	No	Yes
Machorro-Cano et al. [14]	Yes	No	No	Yes
López-Martines et al. [15]	No	Yes	Yes	Yes
Jahan et al. [16]	Yes	Yes	No	Yes
Varlamis et al. [17]	No	Yes	No	Yes
Al-Taie et al. [18]	No	Yes	No	Yes
Cañete-Sifuentes et al. [19]	No	Yes	No	Yes
Duan et al. [20]	Yes	Yes	No	No
Al-Taie et al. [21]	No	Yes	Yes	Yes
Mattos et al. [22]	No	Yes	Yes	Yes
Liu et al. [23]	No	Yes	Yes	Yes
Yawson et al. [24]	No	No	No	Yes
Olowookere et al. [25]	No	No	No	Yes
Cauteruccio and Terracina [26]	No	No	No	Yes
Olmos-Vallejo et al. [27]	Yes	Yes	Yes	Yes
This work	Yes	Yes	Yes	Yes

Five works [15,16,21–23] meet with three criteria. Nevertheless, although [15,21–23] apply SD algorithms and visualization techniques to solve problems in the medical area, they do not consider the comparison of opinions. In contrast, Ref. [16] contemplates the latter as well as visualization techniques in a medical case study, but it does not apply any SD algorithm. Our previous research [27] meets all of the criteria, but it only presented the architecture of the SD module. Given that this paper shows the results of the comparative analysis of five SD algorithms to select the three with the best results that were implemented in the SD module, this work exposes and shows the application, reproducibility, and usefulness of the four criteria mentioned above, which characterize it as original and novel.

3. Methodology

The basic terms of this research and the data sets of medical opinions are described in this section, in addition to the SD algorithms and quality functions used to evaluate their results.

3.1. Basic Definitions

It is widely recognized that data mining tasks can be mainly predictive or descriptive. The former aims to determine the value of a target variable according to the values of other data set attributes. In contrast, the latter searches for patterns in the data, e.g., clusters, associations, or correlations [28]. SDRD has features from both task kinds since its techniques obtain patterns considering labeled data [29]. Subgroup discovery is an SDRD technique that has the objective of finding relevant relationships among the objects of a data set in reference to a target variable [30].

A database D = (I, A) contains a set of instances I and a set of attributes A. For nominal attributes, a selector or basic pattern $(a_i = v_j)$ is a Boolean function $I \rightarrow \{0, 1\}$ which is true when the attribute $a_i \in A$ has the value v_j for the corresponding instance. $\sum$ denotes the set of all selectors.

To describe a subgroup, it is used a description language that usually consists of attribute–value pairs, for instance, typically in conjunctive or disjunctive normal form. A description of a subgroup or (complex) pattern P is therefore given by a set of selectors $P = \{sel_1, \ldots, sel_m\}$, $sel_i \in \sum$, $i = 1, \ldots, m$ that is interpreted as a conjunction, i.e., $P(I) = sel_1 \wedge \ldots \wedge sel_m$ with $length(P) = m$. A pattern is interpreted as the body of a rule. The head of the rule then relies on the target variable. A subgroup $S_P := ext(P) := \{i \in I | P(i) = true\}$, i.e., the size of the subgroup, is the set of the instances covered by the description of subgroup P [31]. SD approaches have been developed considering several types of data and class label attributes, for instance, binary, nominal, or numeric domains [32]. For example, Rule 1 has the selector *rejection_cause* = *social factors* and the size of the subgroup is 4, i.e., four physicians opine that social factors are a cause of rejection in autopsy requests.

Rule 1. If doctors think that a cause or motive for not requesting an autopsy is because of social factors, then they work at Hospital Regional Río Blanco.

3.2. Subgroup Discovery Algorithms

Data sets C and D [12] contain the results of the surveys applied to the medical staff of the three Mexican hospitals. The current characteristics of these data sets are presented in Table 2. In data set C, each instance corresponds to a survey, and each attribute represents every possible answer to each survey question; therefore, data set C is a binary matrix, where $r_{ij} = 1$ if the respondent answered j to the question i, and $r_{ij} = 0$ otherwise. In contrast, in data set D, every attribute belongs to a survey question and an instance includes all of the answers given by the respondent.

Table 2. Characteristics of data sets C and D.

Features	Set C	Set D
Attributes	247	19
Instances	289	47,093
Data type	Nominal–Binary–Asymmetric	Nominal
Description	Binary array <answer, value>	Matrix represented by <question, answer>
Missing values	Yes	No
Out-of-range values	No	No
Inconsistent values	No	No

Table 3 includes the description of each attribute of the data set D. Also, the data set C was used for the tests; this data set contains the hospital identifier and the <response-value> relationship selected by the user.

Table 3. Observed and expected counts.

Name	Description
Id_instancia	Identifier of the instance
Centro_hospitalario	The hospital to which the respondent physician belongs
Área	Medical area
Categoría	Corresponding category
Ult_grado	Last grade
Esc_med_gral	General medical training center
Esc_esp	Training center for medical specialties
Anios_prac	Years of medical practice
Casos	Participation in autopsy cases
Hall_disc	Autopsy findings are inconsistent with clinical diagnoses
Hall_arb	Autopsy findings lead to arbitration cases
Hall_dem	Autopsy findings lead to lawsuits
mcc_aut	Reasons for accepting the autopsy
Mcc_no_aut	Reasons for rejection of the autopsy
Rechazo_fam	Reasons for rejection of the autopsy by the family member
No_hosp	Reasons for insufficient autopsies performed in the hospital
Per_sol_aut	Personnel qualified to request an autopsy
Med_aut	Causes for the doctor to order an autopsy
Fmr_sol_aut	Efficient methods for requesting an autopsy

The VIKAMINE data mining tool (Visual, Interactive, Knowledge-Intensive, Analytics, and MINing Environment, accessed on 26 November 2024, in www.vikamine.org) was used to test five SD algorithms that allowed for the use of categorical class labels. We selected SDMap because it was widely used in the related works, according to our previous study [27]. The other four algorithms were used because of their efficiency [31]. VIKAMINE is a specialized environment for discovering and analyzing subgroups [33]. The class considered for these tests was the attribute *Centro_hospitalario*, with the H1 values for the H.R.R.B., H2 for the H.G.S.B.T, and H3 for H.G.Z.53. The algorithms used for the tests were as follows.

- **SDBeamSearchDisjunctive**: It starts with a subgroup discovery problem and an initial subgroup description. In each iteration, a selector is included in the subgroup description. Then, a quality function is utilized to measure the quality of the subgroup description. For each beam search iteration, the best k subgroup descriptions are used in the next iteration until the quality of the best k subgroup descriptions is no longer improved. In this case, subgroups contain conjunctions and/or selector disjunctions [34].
- **SimpleDFS**: This algorithm uses optimistic estimates to reduce as much of the search space as possible, and then it determines the order in which nodes expand through depth-first search (DFS). It uses FP (Frequent Pattern) trees to accelerate the estimation of the parameters p (relative frequency) and n (size) of a subgroup [35].
- **SDMap**: It ensures the identification of all interesting subgroup patterns included in a data set; SDMap utilizes the widely used FP-growth algorithm for association rule mining with adjustments for the SD task [36].
- **BSD (Bitset-based SD)**: This algorithm allows for the efficient handling of binary, nominal, and numeric target variables. It uses a vertical data structure that employs bit sets (bit vectors) for selectors and instances that reflect the current subgroup hypothesis, and another array for the (numerical) values of the target variable. Thus, the search—that is, the improvement of the patterns—is efficiently implemented by logical AND operations in the corresponding bitsets, so that the values of interest are recovered directly [31].
- **BeamSearch**: It is based on finding subgroups of a given size that can be null; after several iterations, BeamSearch finds the best subgroups [37].

3.3. Quality Functions

SD utilizes a quality function to determine how interesting a subgroup is. It uses four parameters for the quality calculation of the subgroup: true positive tp (instances with the target variable t in the subgroup s), false positive fp (instances without the variable t in the subgroup s), and the positives TP and negatives FP concerning the target variable t in the general population of size N. Therefore, the parameters of the subgroups are calculated as observed in (1) to (7) [36]:

$$n = count(s), \tag{1}$$

$$tp = support(s) = count(s \wedge t), \tag{2}$$

$$fp = n - tp, \tag{3}$$

$$p = \frac{tp}{tp + fp}, \tag{4}$$

$$TP = count(t), \tag{5}$$

$$FP = N - TP, \tag{6}$$

$$p_0 = \frac{TP}{TP + FP}. \tag{7}$$

Next, the quality functions used in the tests are described. Although we used all of the functions provided by the VIKAMINE framework, we present the functions with better results.

- **ChiSquareQF:** The quality function based on Chi-square is calculated with (8):

$$\text{ChiSquareQF} = \sum_{i=1}^{4} \frac{(O_i - E_i)^2}{E_i} \tag{8}$$

where O_i and E_i refer to the observed and expected values, respectively. These are obtained according to (9) to (16) shown in Table 4:

Table 4. Observed and expected counts.

Observed Value		Expected Value	
$O_1 = tp,$	(9)	$E_1 = \frac{n}{N} * TP,$	(13)
$O_2 = TP - tp,$	(10)	$E_2 = \frac{N-n}{N} * TP,$	(14)
$O_3 = fp,$	(11)	$E_3 = \frac{n}{N} * FP,$	(15)
$O_4 = FP - fp,$	(12)	$E_4 = \frac{N-n}{N} * FP.$	(16)

For example, the BeamSearch algorithm with the ChiSquareQF quality function found Rule 2:

Rule 2. If physicians consider that not enough autopsies are performed in the hospital because of the lack of human resources, then they work at Hospital Regional Río Blanco.

Table 5 shows the contingency table for Rule 2. For this rule, $N = 289$, it is the number of applied surveys; $n = 127$, because 127 doctors opined that not enough autopsies are performed in the hospital because of lack of human resources, $tp = 39$, i.e., 39 physicians of H.R.R.B. opined the same, $fp = 127 - 39 = 88$, $TP = 161$, since 161 doctors of the 289 survey respondents belong to the H.R.R.B. Therefore, the expected values are obtained according to Equations (13)–(16).

Table 5. Contingency table for Rule 2.

Cause Because Not Enough Autopsies Are Performed at the Hospital Regional Río Blanco	H.R.R.B.	Other Hospitals	Count
Because of the lack of human resources	$tp = 39$	$fp = 88$	$n = 127$
Because of other causes	$TP - tp = 122$	$FP - fp = 40$	$N - n = 162$
Count	$TP = 161$	$FP = 128$	$N = 289$

$$E_1 = \frac{127}{289} * 161 = 70.75$$
$$E_2 = \frac{162}{289} * 161 = 90.25$$
$$E_3 = \frac{127}{289} * 128 = 56.25$$
$$E_4 = \frac{162}{289} * 128 = 71.75$$

Then, the ChiSquareQF value is calculated using Equation (8):

$$\begin{aligned} \text{ChiSquareQF} &= \frac{\left(39 - 70.75^2\right)}{70.75} + \frac{\left(122 - 90.25^2\right)}{90.25} + \frac{\left(88 - 56.25^2\right)}{56.25} + \frac{\left(40 - 71.75^2\right)}{71.75} \\ &= 14.25 + 11.17 + 17.92 + 14.05 = 57.39. \end{aligned}$$

- **WRAccQF:** Weighted relative accuracy measures how unusual a rule is, defined as the balance between its coverage (percentage of doctors with these reviews) and its accuracy gain. It is calculated with (17) [38].

$$\text{WRAccQF} = \frac{n}{N} * (p - p_0) \tag{17}$$

where p is the relative frequency of the target variable (selected hospital) in the subgroup (physicians with such opinions), p_0 is the relative frequency of the target variable in the total population, N is the size of the total population, and n is the size of the subgroup.

For instance, the BSD algorithm found Rule 3.

Rule 3. If physicians agree that autopsy discoveries raise arbitration cases, then they work at Hospital Regional Río Blanco.

In this case, $N = 289$, since it is the total number of surveys applied (161 from H.R.R.B.), $n = 131$, *i.e.*, 131 doctors opined this (91 from H.R.R.B.), $p = \frac{91}{131} = 0.695$, $P_0 = \frac{161}{289} = 0.557$; therefore, with Equation (17), we obtain:

$$\text{WRAccQF} = \frac{131}{289} * (0.695 - 0.557) = 0.453 * 0.138 = 0.06.$$

- **BinomialQF:** The binomial test quality function compares the observed frequencies (opinions) of the two categories of a dichotomous variable (selected hospital vs. other hospitals) with expected frequencies in a binomial distribution with a specified probability parameter of 0.5 (equal opinions), as seen in (18) [31].

$$\text{BinomialQF} = \sqrt{n} * (p - p_0) \tag{18}$$

For example, the SDMap algorithm obtained Rule 1.

Rule 1. If doctors think that a cause or motive for not requesting an autopsy is because of social factors, then they work at Hospital Regional Río Blanco.

In this case, $n = 4$, the four physicians work at H.R.R.B.; therefore, $p = \frac{4}{4} = 1$, $p_0 = \frac{161}{289} = 0.557$; thus, according to Equation (18):

$$\text{BinomialQF} = \sqrt{4} * (1 - 0.557) = 2 * 0.443 = 0.89.$$

- **PrecisionQF:** It measures the compensation of a subgroup between the number of examples classified correctly and the unusualness of its distribution. Calculated with (19).

$$\text{PrecisionQF} = \frac{TP}{FP + g} \tag{19}$$

where g is utilized as a generalization parameter, typically set between 0.5 and 100 [30].

For instance, for Rule 2 the PrecisionQF is obtained using Equation (19) and $g = 0.5$ as:

$$\text{PrecisionQF} = \frac{161}{128 + 0.5} = \frac{161}{128.5} = 1.25$$

- **RelativeGainQF:** It compares the average values of the target variable in the subgroup and the total population by measuring the relative gain [39], as seen in (20).

$$\text{RelativeGainQF} = \frac{p - p_0}{p_0 * (1 - p_0)} \tag{20}$$

The RelativeGainQF of Rule 3 is calculated with Equation (20) as follows:

$$\text{RelativeGainQF} = \frac{0.695 - 0.557}{0.557 * \ (1 - 0.557)} = \frac{0.138}{0.247} = 0.56.$$

- **SimpleBinomialQF:** A simplified version of the binomial function [40], it is obtained with (21):

$$\text{SimpleBinomialQF} = n^2 * (p - p_0) \tag{21}$$

For example, Equation (21) is used to obtain the SimpleBinomialQF of Rule 1 as:

$$\text{SimpleBinomialQF} = 4^2 * (1 - 0.557) = 16 * 0.443 = 7.09.$$

- **StdQF:** It is a generalization of the BinomialQF, AddedValueQF, and SimpleBinomialQF functions, as shown in (22):

$$\text{StandardQF} = n^a * (p - p_0) \tag{22}$$

When a = 0.5, (22) defines BinomialQF, if a = 0, then (22) defines AddedValueQF, or else if a = 2, then (22) defines SimpleBinomialQF [31].

The StdQF of Rule 1 is obtained with Equation (22) considering a = 0.5, then a = 0, and finally a = 2, as follows:

$$\text{StandardQF} = 4^{0.5} * (1 - 0.557) = 0.89$$

$$\text{StandardQF} = 4^{0} * (1 - 0.557) = 0.443$$

$$\text{StandardQF} = 4^{2} * (1 - 0.557) = 7.09$$

- **AdjustedResidualQF:** It multiplies the quality StdQF of the group by a penalty [41], calculated with (23):

$$\text{AdjResQF} = \text{StdQF} * \frac{1}{\left(p_0 * n * (1 - p_0) * \left(1 - \frac{n}{N}\right)\right)} \tag{23}$$

The AdjustedResidualQF of Rule 1 using the first StdQF is obtained using Equation (23).

$$\begin{aligned}\text{AdjResQF} = \text{StdQF} * &\frac{1}{\left(0.557 * 4 * (1 - 0.557) * \left(1 - \frac{4}{289}\right)\right)} \\ &= 0.89 * \frac{1}{2.228 * 0.443 * (1 - 0.014)} \\ &= 0.89 * \frac{1}{2.228 * 0.443 * 0.986} = 0.89 * \frac{1}{0.973} = 0.89 * 1.028 \\ &= 0.91.\end{aligned}$$

- **DyadicLiftCompletedQF:** It refers to the Lift quality function, obtained with (24), where T_n specifies a minimum size constraint for the subgroup [38].

$$\text{Lift} = \frac{p}{p_0},\ n \geq T_n \tag{24}$$

For instance, the Lift of Rule 3 is computed with Equation (24) considering $T_n = 100$ as:

$$\text{Lift} = \frac{0.695}{0.557}, 131 \geq 100 = 1.25.$$

- **AddedValueQF:** Also called gain quality function (Gain) [42], it is calculated using (25):

$$\text{AddedValueQF} = p - p_0 \tag{25}$$

Equation (25) is used to obtain the AddedValueQF of Rule 1 as follows:

$$\boldsymbol{AddedValueQF} = \mathbf{1} - \mathbf{0.557} = \mathbf{0.443}.$$

4. Experimental Findings

The subgroups obtained using the SD algorithms in the survey data sets C and D were evaluated considering the quality functions described above. Experiments were performed using computer equipment with an AMD Ryzen 5 4600H 3.00 GHz processor, 16 GB of RAM, and 1 TB SSD. Each algorithm was evaluated using the following metrics:

- **Class label:** The hospital to analyze.
- **Quality function:** Refers to the quality function utilized to evaluate the subgroups obtained by the algorithm.
- **Search algorithm:** Algorithm specialized in SD.
- **Number of Subgroups:** Number of subgroups to generate.
- **Runtime:** Time in seconds taken by the algorithm to obtain the results; it should be mentioned that this value is the average of 100 test executions.
- **Average result of the quality function**: Given all of the values of the quality function, the average was obtained for its evaluation.

4.1. Analysis of Data Sets C and D Considering 50 Subgroups

Figures 1–4 compare the performance of the SDMap, BSD, BeamSearch, SDBeamSearchDisjunctive, and SimpleDFS algorithms with the three values for the class label *Centro_hospitalario*, H1, H2, and H3; for the three analyzed hospitals, this test was performed with data sets C and D. Figure 1 shows the average quality function values for 50 subgroups obtained in the data set C. Figure 2 illustrates the runtime in seconds of the algorithms taken to build the models.

The average values of each quality function for 50 subgroups found in the data set D with SDMap, BSD, BeamSearch, and SDBeamSearchDisjunctive algorithms are presented in Figure 3. Also, the runtime of each algorithm is exhibited in Figure 4. SimpleDFS did not discover any subgroup in this case.

4.2. Analysis of Data Sets C and D Considering 20 Subgroups

Figures 5–8 compare the performance of the SD algorithms for the three hospitals with the data sets C and D, but now contemplating 20 subgroups. Figure 5 illustrates the average quality of the 20 subgroups for the data set C yielded with SDMap, BSD, BeamSearch, BeamSearchDisjunctive, and SimpleDFS. Figure 6 shows the runtime taken by the algorithms to discover the subgroups.

The average quality of the 20 subgroups found with SDMap, BSD, BeamSearch, and SDBeamSearchDisjunctive are presented in Figure 7, and the runtime that each algorithm took to build the models is shown in Figure 8. Again, SimpleDFS did not obtain any subgroup in this experiment.

In this way, all of the relevant tests were carried out with each possible combination, that is, 20 or 50 subgroups, the 5 specialized SD algorithms mentioned and described above, as well as with each quality function. These experiments provide us with the necessary knowledge to select the best SD algorithms to compare the medical opinions about the autopsy decreasing rates in Mexican hospitals. The algorithms with the best results were SDMap, BSD, and BeamSearch.

In the next section, we introduce the architecture of the SD module and its functionality. The algorithms SDMap, BSD, and BeamSearch with the quality functions BinomialQF, WRAccQF, and ChiSquareQF were implemented in the SD module to find 20 and 50 subgroups in the data sets C and D. The subgroups were presented in natural language to the pathologists and in a graphical way to easily filter the most relevant for the specialists.

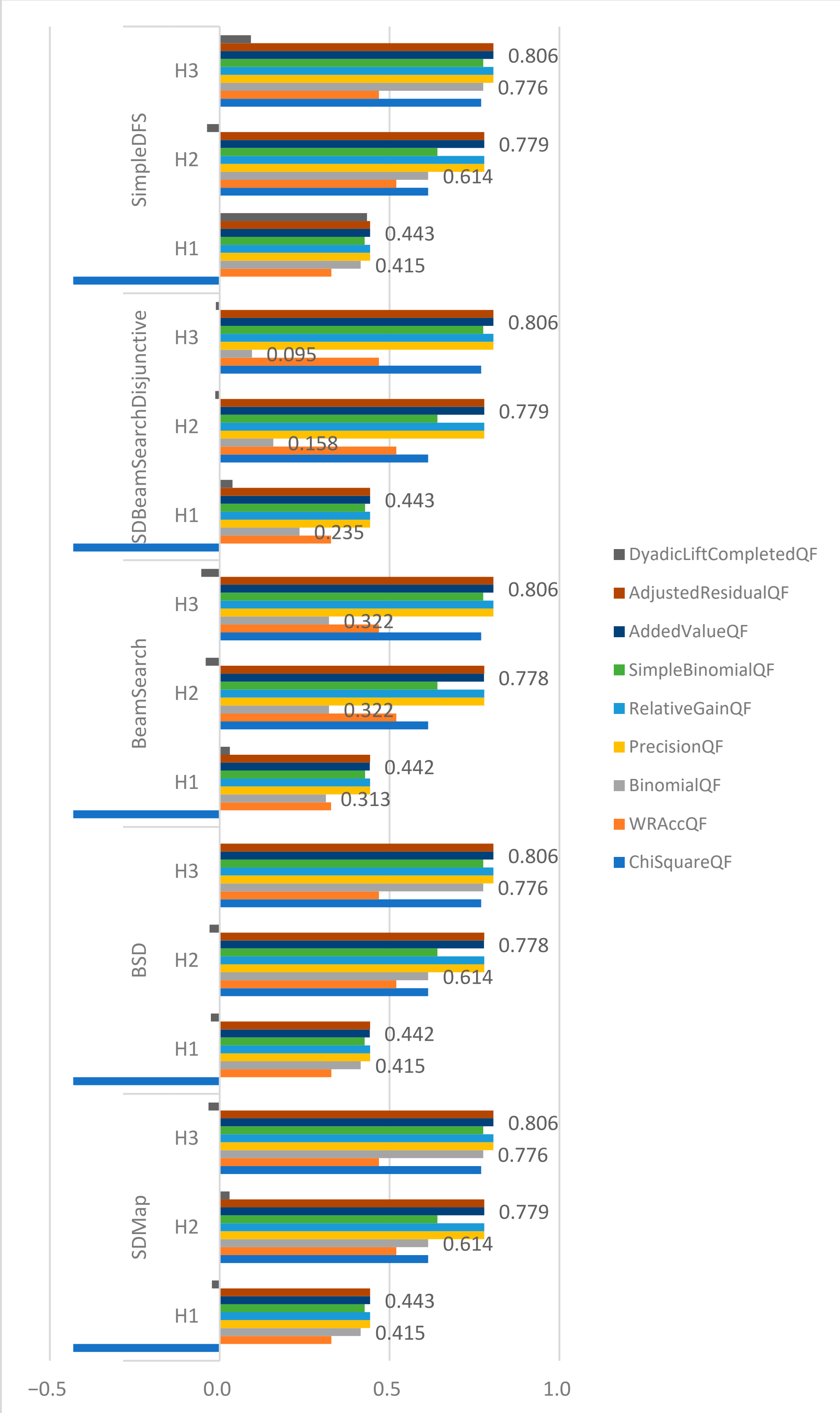

Figure 1. Quality value comparison of SD algorithms in data set C with 50 subgroups.

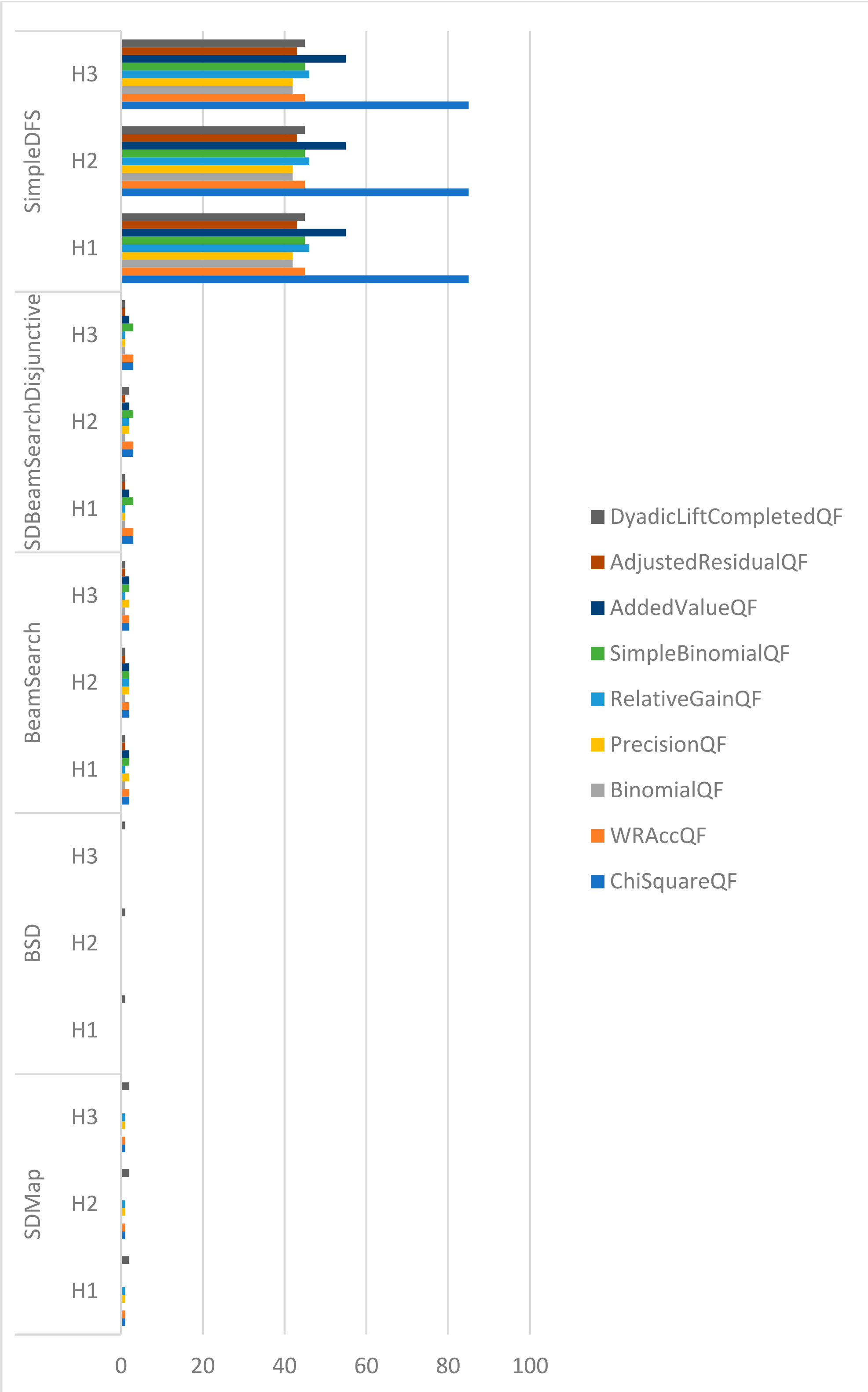

Figure 2. Run-time comparison of SD algorithms in data set C with 50 subgroups.

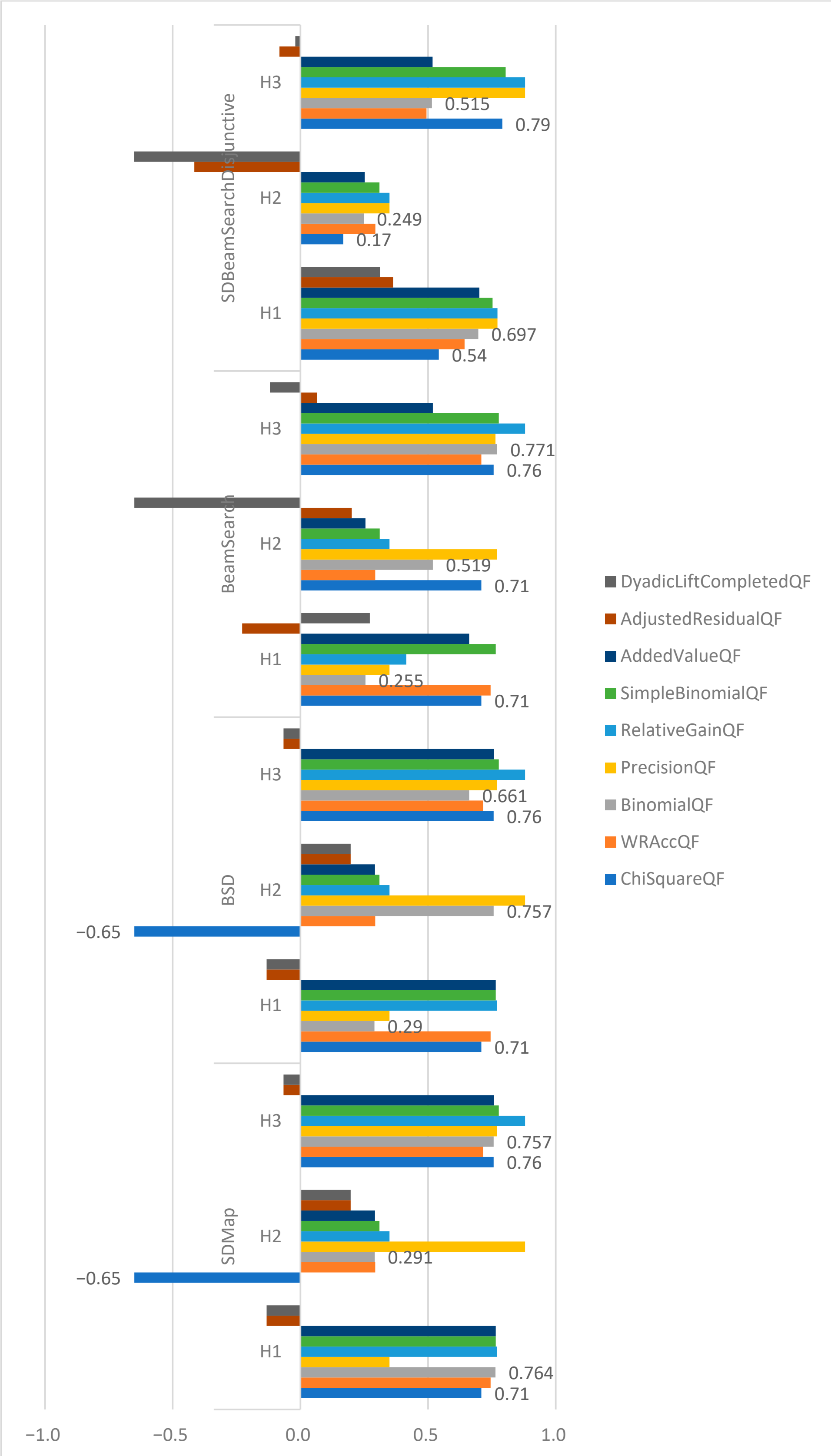

Figure 3. Quality value comparison of SD algorithms on data set D with 50 subgroups.

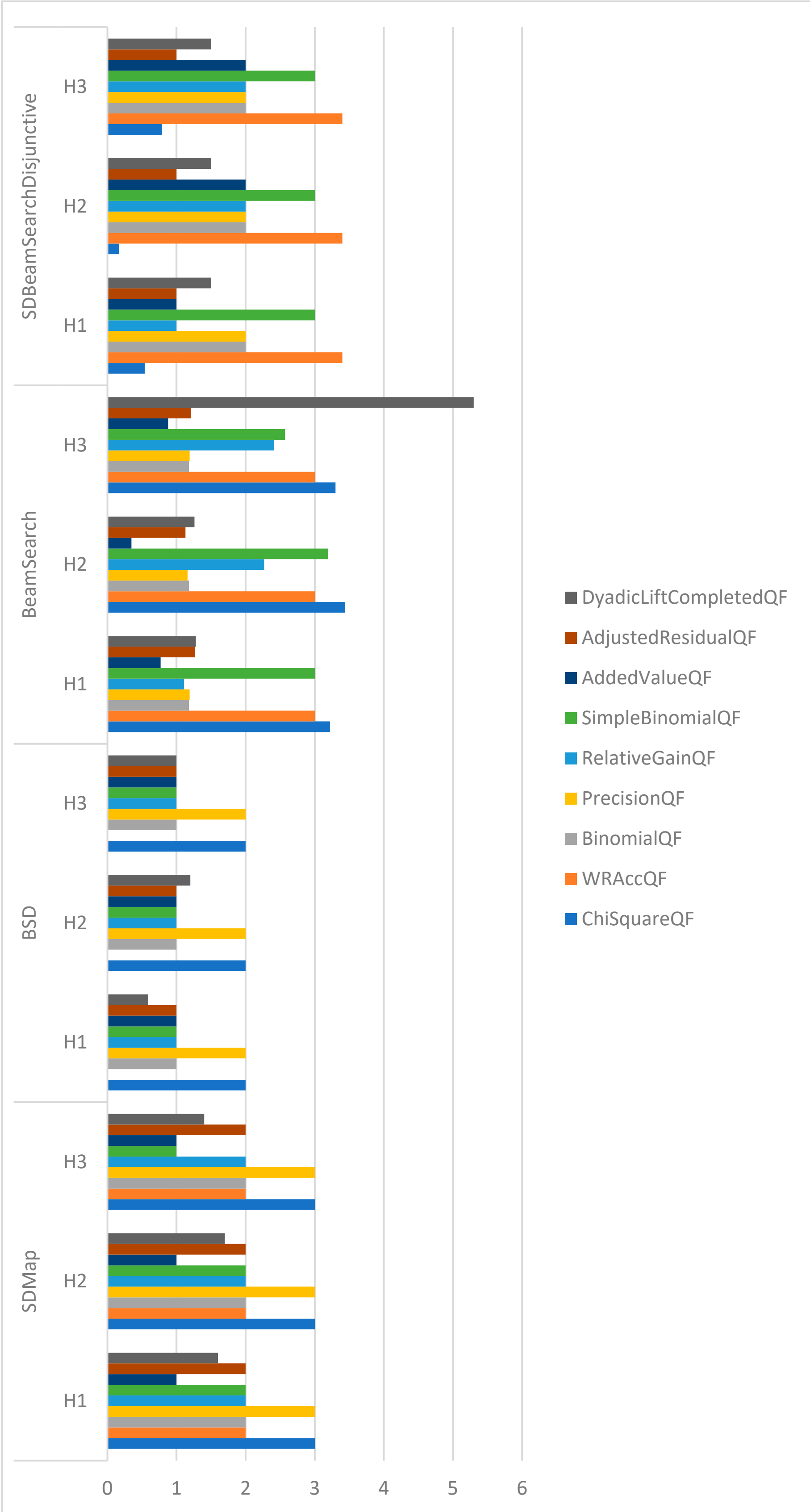

Figure 4. Run-time comparison of SD algorithms in data set D with 50 subgroups.

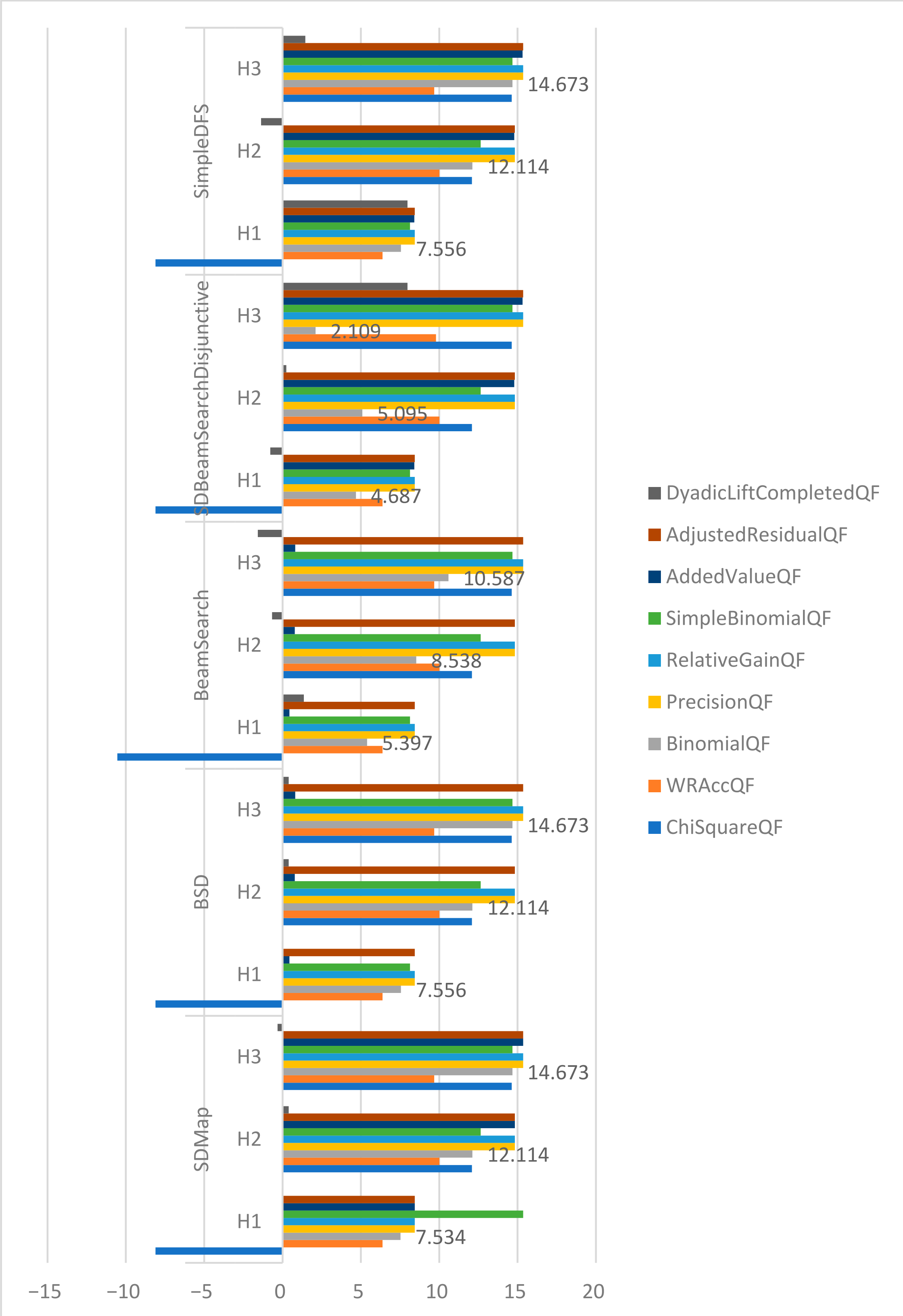

Figure 5. Quality value comparison of SD algorithms in data set C with 20 subgroups.

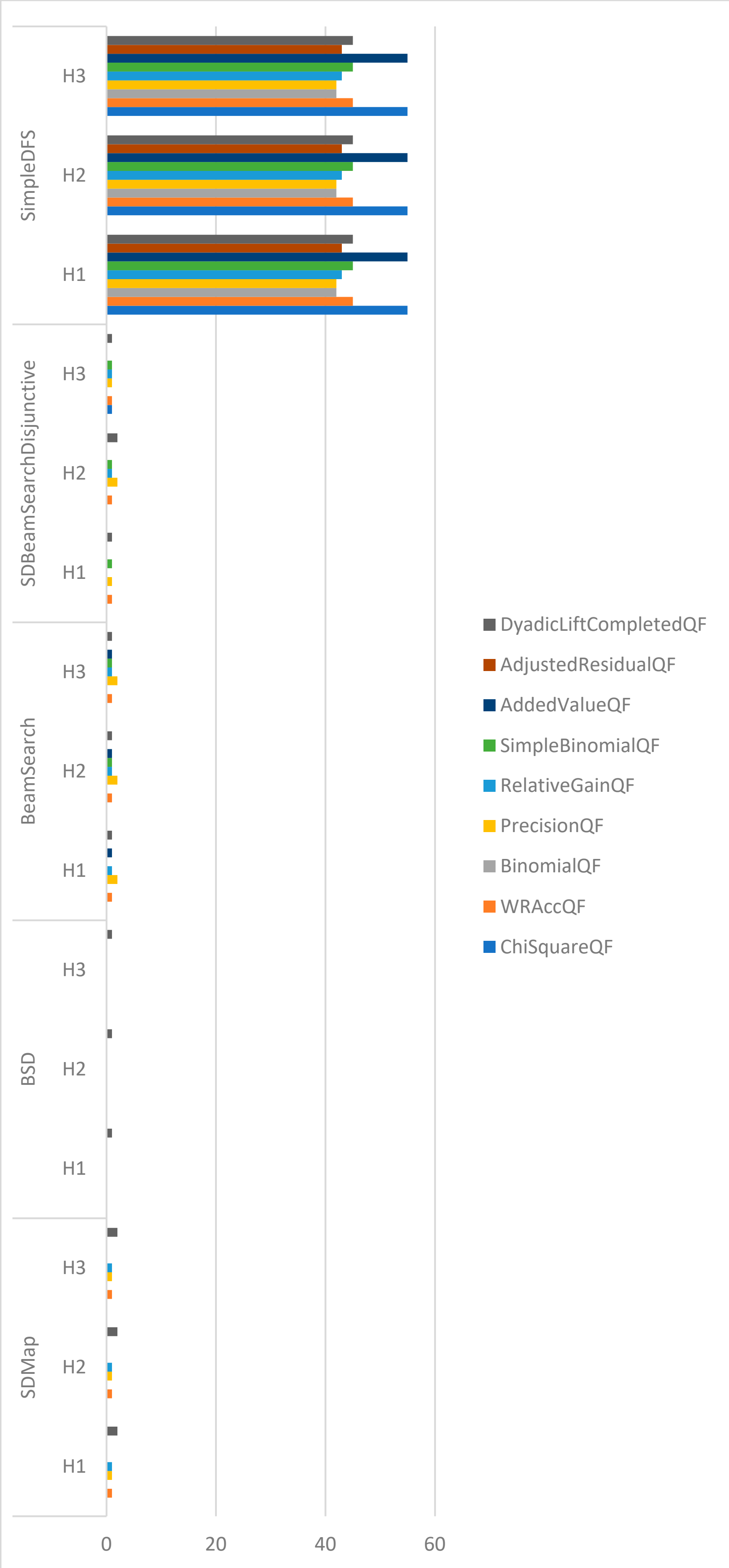

Figure 6. Run-time comparison of SD algorithms in data set C with 20 subgroups.

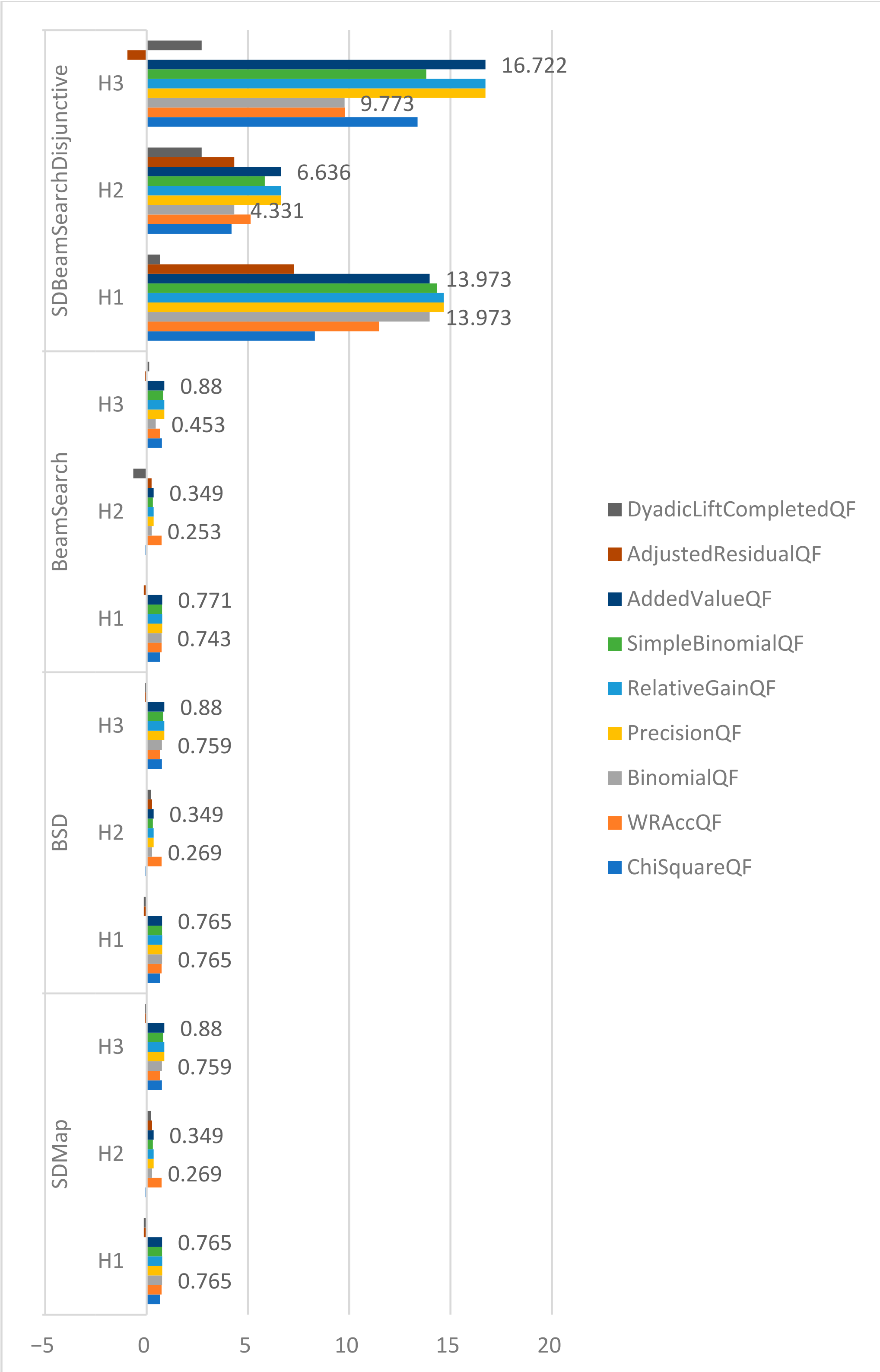

Figure 7. Quality value comparison of SD algorithms on data set D with 20 subgroups.

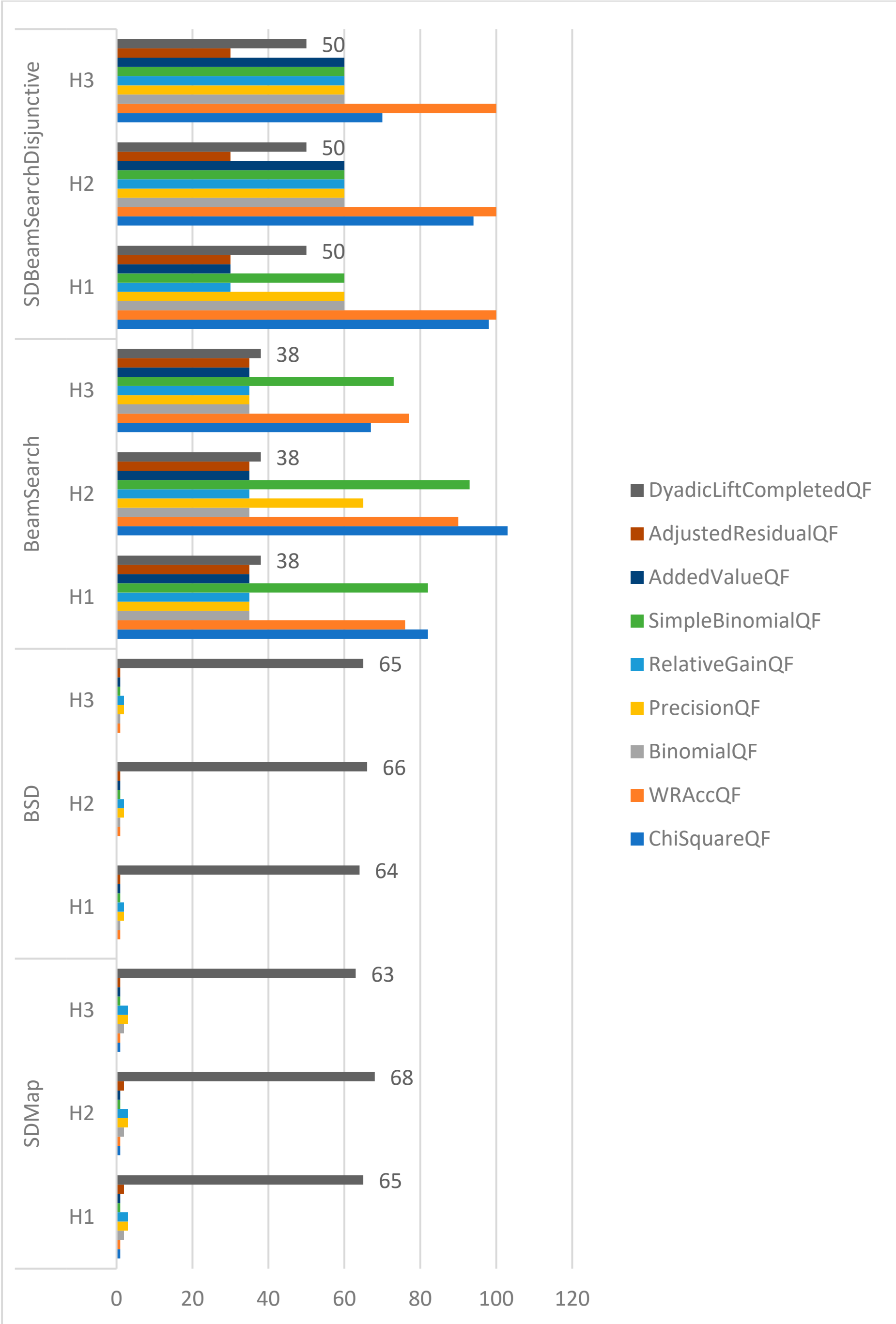

Figure 8. Run-time comparison of SD algorithms in data set D with 20 subgroups.

5. SD Module Description

Figure 9 shows the architecture of the SD module. It is based on the Model-View-Controller (MVC) pattern. The description of each component of the architecture is given next.

- **Model:** Models are the elements that interact with the data managed by the application, i.e., the medical opinions about the decreasing rates of autopsies. They are responsible for managing these data, using a database to perform queries and apply filters.
- **View:** Views are the components responsible for generating the visualization of the user interface, presenting screens, windows, and forms to the end user, using XHTML (eXtensible HyperText Markup Language) files that incorporate JSF (JavaServer Faces) tags and elements from the PrimeFaces library.

- **Controller:** This layer houses the business logic of the application, i.e., the core functionalities. In general terms, it is responsible for receiving, managing, and executing the instructions sent to it. It includes the JSF servlet, which facilitates communication between the model and the view, selecting the corresponding view according to the instructions being processed.

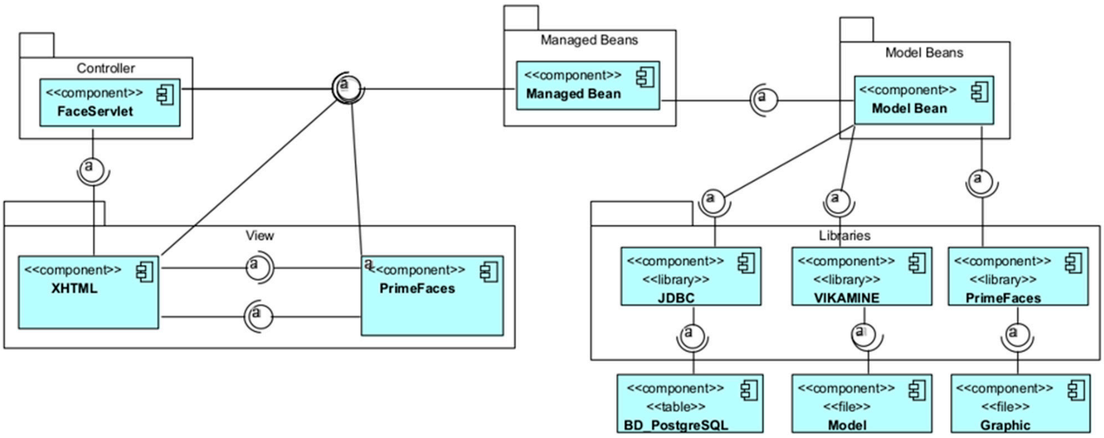

Figure 9. SD module architecture.

After the analysis and selection of the three most efficient algorithms that, together with the quality functions, provide the best results, they were implemented in an SD module that was added to the system previously developed and presented in [12] for the generation of the corresponding rules for each hospital. The technologies used to develop the SD module were the Java programming language with the JavaServer Faces (accessed on 24 November 2024, in https://www.oracle.com/java/technologies/javaserverfaces.html) and PrimeFaces frameworks (accessed on 24 November 2024, in https://www.primefaces.org), the integrated development environment NetBeans version 12.2, and the database management system PostgreSQL version 13. The SD module interprets the rules into a natural language for specialists to perform an analysis without being experts in the data mining area; Figure 10 shows the form to start creating subgroups.

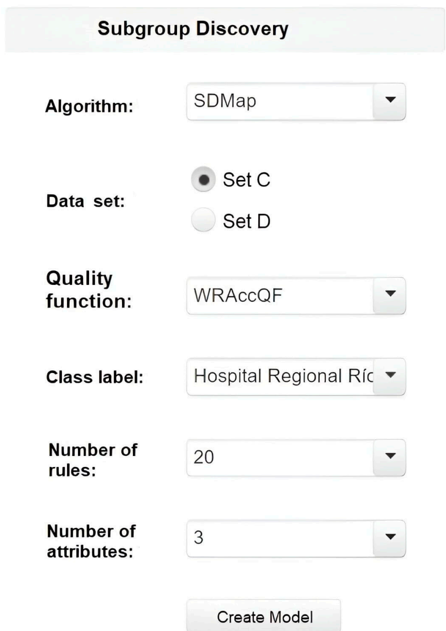

Figure 10. Form for obtaining the rules.

As seen in Figures 11 and 12, the specialist has the option to see the rules generated using the SD module that have not been or that have already interpreted into a natural language. Likewise, to make a more interesting analysis and selection of rules for experts in a faster and more visual way, a "Visual Analysis" section was added to the SD module; this section generates a graph from the rules obtained, as seen in Figure 13.

− Uninterpreted rules

No. Rule	Rule	Size	Quality function value
1	S{p13_1=S}	53.0	0.078
2	S{p16_8=S}	55.0	0.077
3	S{p4_2=S, p11_1=S}	94.0	0.071
4	S{p13_1=S, p10_1=S}	47.0	0.069
5	S{p16_8=S, p10_1=S}	47.0	0.069
6	S{p4_2=S, p9_4=S, p11_1=S}	62.0	0.067
7	S{p4_2=S, p9_4=S}	73.0	0.067
8	S{p4_2=S}	131.0	0.066
9	S{p13_1=S, p11_1=S}	44.0	0.064
10	S{p16_8=S, p11_1=S}	41.0	0.063

Figure 11. Generation of SD rules without interpretation.

Interpretation of the rules

No.	Rule
Rule: 1	If the doctors do not comment, then they are from the Hospital Regional Río Blanco. This rule has a weighted relative accuracy of: 0.078, the size of this subgroup is: 53.0 and its overall percentage of: 18%
Rule: 2	If the doctors studied general medicine in High Specialty at IMSS, then they are from the Hospital Regional Río Blanco. This rule has a weighted relative accuracy of: 0.077, the size of this subgroup is: 55.0 and its overall percentage of: 19%.
Rule: 3	If the doctors agree that the autopsy findings give rise to arbitration cases and consider interest as the reason for requesting an autopsy, then they belong to the Hospital Regional Río Blanco. This rule has a weighted relative accuracy of: 0.071, the size of this subgroup is: 94.0 and its overall percentage of: 32%.
Rule: 4	If the doctor do not comment and allege that the doctor is the appropriate personal to order an autopsy, then they are from the Hospital Regional Río Blanco. This rule has a weighted relative accuracy of 0.069, the size of this subgroup is: 47.0 and its overall percentage is: 16%
Rule: 5	If the doctors studied general medicine in High Specialty at IMSS and allege that the doctor is the appropriate personnel to order an autopsy, then they are from the Hospital Regional Río Blanco. This rule has a weighted relative accuracy of: 0.069, the size of this subgroup is: 47.0 and its overall percentage of: 16%.

Figure 12. Interpretation of the SD rules.

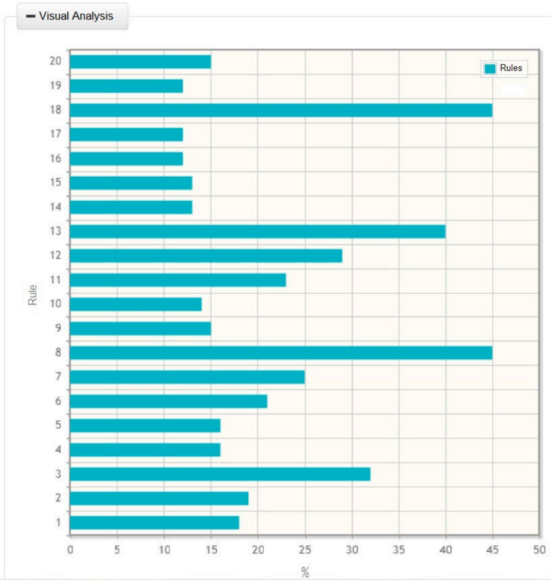

Figure 13. Visual analysis.

Similarly, if the specialist needs to store all of this information for future analysis, the SD module can present the interpreted rules in a PDF file. This document includes the graph generated using the SD module based on the obtained rules, all of the parameters that the specialist selected for the creation of the SD rules, with a description of the quality function, since the pathology area of the H.R.R.B. requested these data, and, subsequently, all of the rules generated using the SD module already interpreted in the natural language, as shown in Figure 14.

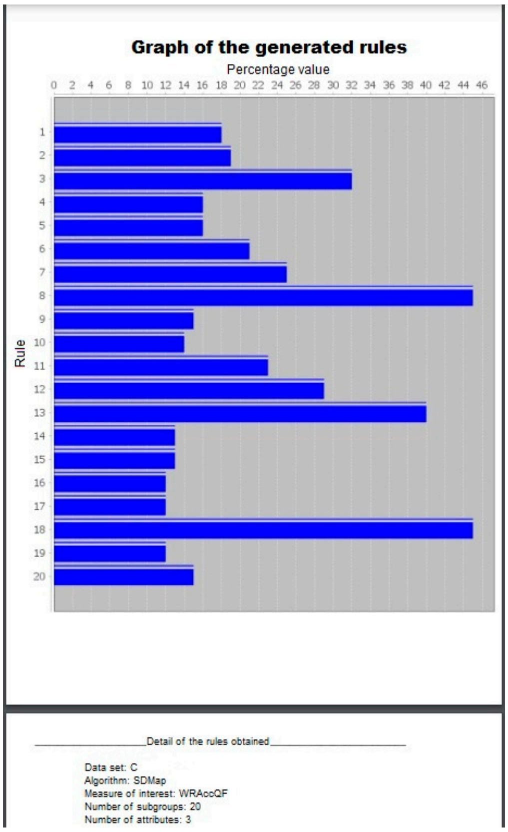

Figure 14. PDF generation.

The developed SD module was validated by a pathology specialist who analyzed and evaluated each rule obtained. The pathologist decided what rules were interesting based on his experience. Generally, the most interesting rules for the pathologist were those containing more than one selector, for example, Rule 3 of Figure 11. The rules discovered using the SDMap algorithm with ChiSquareQF and WRAccQF quality functions achieved 100% and 98.33% approval for C and D data sets, respectively.

Finally, the rules obtained using the DS module allowed for the pathology specialists to find similarities and differences between the medical opinions of the three hospitals on the reasons, motives, and circumstances of the decrease in autopsies, e.g., the three algorithms with ChiSquareQF and BinomialQF quality functions agree that 43% of the doctors in the three hospitals consider that not enough autopsies are performed due to a lack of human resources. In contrast, with BinomialQF, it was discovered that 20% of doctors in only two hospitals considered the lack of interest in the pathology area as a reason.

6. Discussion

This section provides the explanation of Figures 1–8 and the theoretical and practical implications of this research. Also, it includes information about a limitation of this study.

Figure 1 shows that SDMap surpassed the other algorithms with DyadicLiftCompletedQF for the hospital H2. SDMap also performed better than BSD and BeamSearch for the hospitals H1 and H2 with AddedValueQF. In addition, SDMap and BSD discover subgroups with higher quality than BeamSearch and BeamSearchDisjunctive with BinomialQF for the three hospitals. In contrast, BeamSearch overcame SDMap, BSD, and SimpleDFS with SimpleBinomialQF for the hospital H1. Therefore, during the analysis, the BSD, SDMap, and BeamSearch algorithms presented the most optimal comparison results and obtained the 50 subgroups in a time range between 0 and 2 s; SimpleDFS was the slowest algorithm because it recorded a time greater than 40 s in all of the executions.

Figure 3 shows that BeamSearch obtained 50 subgroups with better quality considering BinomialQF for the hospital H3 and ChiSquareQF for the hospital H2 in the data set D. Also, SDMap, BSD, and BeamSearch overcame SDBeamSearchDisjunctive for hospital H1 with ChiSquareQF and WRAccQF. In addition, Figure 4 exhibits that SDMap and BSD are the fastest algorithms to discover the 50 subgroups in the data set D. These results imply that SDMap, BSD, and BeamSearch demonstrate better performance in finding 50 subgroups in the data set D than the other algorithms.

Figure 5 shows that the 20 subgroups discovered by BSD and SimpleDFS had better quality with BinomialQF for hospital H1. Also, the quality value of the subgroups found by SDMap, BSD, and SimpleDFS with BinomialQF for the hospitals H2 and H3 is greater than the average value of the rest of the algorithms. Moreover, Figure 6 illustrates that SimpleDFS is the slowest algorithm. Thus, again SDMap, BSD, and BeamSearch were superior to their counterparts.

Figure 7 illustrates that SDMap and BSD obtain subgroups with higher quality than BeamSearch using BinomialQF for the three hospitals and with AdjustedResidualQF and DyadicLiftCompletedQF for the hospital H2. In contrast, BeamSearch overcame SDMap and BSD with AddedValueQF for the hospital H1 and with DyadicLiftCompletedQF for the hospitals H1 and H3. Again BSD, SDMap, and BeamSearch obtained better results, since although Figure 3 shows that the subgroups discovered with SDBeamSearchDisjunctive presented higher quality, Figure 8 shows that it was the slowest in most cases, except when the DyadicLiftCompletedQF quality function was used. SimpleDFS did not receive rules in this data set. These experiments justify the selection of BSD, SDMap, and BeamSearch for their implementation in the SD module presented in this paper.

Regarding the theoretical and practical implications of this work, we performed a comparative analysis of five SD algorithms provided by the VIKAMINE data mining tool considering nine quality functions. The algorithms were evaluated with 20 and 50 subgroups in data sets C and D. Also, we integrate information about these quality functions and provide an example of each one. To the best of our knowledge, this is the first work that performed such integration. The selected algorithms were implemented in a SD module that facilitates the comparison of medical opinions about autopsy decrease to the pathologists, providing rules in natural language and in a graphical way.

A limitation of this study is that we only consider three Mexican public hospitals; therefore, they lack sufficient financial resources to enhance their teaching service, thus, the opinions of the medical staff are a consequence, in part, of their academic formation and experience obtained in other hospitals; nevertheless, we identify that the physicians who answered the survey studied in different universities; this allowed us to obtain different perspectives on the decreasing rates of autopsies in hospitals.

7. Conclusions and Future Work

This paper presents the results of analyzing two data sets with the opinions of physicians on the reduction in autopsies in Mexican hospitals, applying five SD algorithms together with nine quality functions, with the aim of finding the most suitable algorithms to be implemented in an SD module to find the differences or similarities between these opinions. The most successful SD algorithms were SDMap, BSD, and BeamSearch, and BSD was the fastest. Similarly, SDMap was the best algorithm evaluated subjectively by a pathologist.

The three selected algorithms (SDMap, BSD, and BeamSearch) with ChiSquareQF and BinomialQF quality functions found that 43% of the doctors in the three hospitals considered that not enough autopsies were performed due to lack of human resources, while with BinomialQF, it was discovered that 20% of doctors in only two hospitals think that it is because of a lack of interest in the pathology area.

Knowing the precise causes of the decline in autopsies allows for specialists to make sound decisions to increase this practice. By directly addressing the causes of the problem, it facilitates its effective and lasting resolution. In the future, it is desired to perform the same tests, but applying contrast set mining in more hospitals to visualize the differences or similarities between the results and previous work.

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Data Availability Statement: Data are contained within the article.

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