Identifying the Severity of Heart Valve Stenosis and Regurgitation Among a Diverse Population Within an Integrated Healthcare System: A Natural Language Processing Approach

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Abstract

Background: Valvular heart disease (VHD) is a leading cause of cardiovascular morbidity and mortality. Administrative diagnostic codes are unable to capture the completeness of VHD.

Objective: To develop a natural language processing (NLP) algorithm to identify patients with valve stenosis and regurgitation from echocardiography reports within a large integrated healthcare system.

Methods: We utilized the reports from echocardiograms performed at Kaiser Permanente Southern California between 1/1/2011-12/31/2022. Related terms/phrases of heart valve stenosis and regurgitation and their severities were compiled from literature and enriched with input from clinicians. An NLP algorithm was iteratively developed and fine-trained via multiple rounds of chart review followed by adjudication. The developed algorithm was applied to 200 annotated echocardiography reports to assess its performance, then the study echocardiography reports.

Results: At report level, valve lesions identified included 111,300 (9.1%) aortic stenosis, 20,246 (1.7%) mitral stenosis, 397 (0.03%) tricuspid stenosis, 2,585 (0.2%) pulmonic stenosis, 345,115 (28.2%) aortic regurgitation, 802,103 (65.5%) mitral regurgitation, 903,965 (73.8%) tricuspid regurgitation, and 286,903 (23.4%) pulmonic regurgitation. Males had a higher frequency of aortic stenosis and all four valvular regurgitations while females had more mitral stenosis, tricuspid stenosis, and pulmonic stenosis. Non-Hispanic whites had the highest frequency among all four valvular stenosis and regurgitations. Frequencies of aortic stenosis, mitral stenosis, and regurgitation of all heart valves were increased with age. Validation of the NLP algorithm against the 200 annotated echocardiography reports showed excellent precision, recall, and F1-scores.

Conclusions: The developed and validated NLP computerized algorithm could support clinical research and monitoring of VHD.

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Conclusions: The developed and validated NLP computerized algorithm could support clinical research and monitoring of VHD.

Introduction

Valvular heart disease (VHD) is a leading cause of cardiovascular morbidity and mortality worldwide [1-3] and poses a substantial healthcare and economic burden on healthcare systems [4, 5]. The prevalence of VHD, especially aortic stenosis, is expected to rapidly increase in the United States and Europe due to population aging [4, 5]. Accurate assessments of the burden of VHD are increasingly relevant as the treatment options for these patients continue to expand. VHD research based on administrative diagnostic codes showed incomplete identification [6] or inaccuracy of coding [7]. Accurate and complete identification of VHD based on information from echocardiography reports other than diagnosis codes have the potential to facilitate patient care and VHD-related cardiovascular research.

Advances in diagnostic imaging technologies have greatly improved the precision and efficiency of assessing heart valve disorders [8, 9]. Echocardiography is the primary imaging modality for evaluating valve structure and function and assessing the severity and hemodynamic consequences of heart valve disease. Transthoracic echocardiogram (TTE) provides key insights into the mechanisms of heart valve disease [8]. The wealth of data and information generated by the interpretations of the echocardiographic studies significantly aid clinical management and research. While the format of echocardiography reports is often templated, the content in each section remains as free text. This presents a challenge for systematic analysis, necessitating advanced natural language processing (NLP) techniques to transform this unstructured data into structured and analyzable information [10].

Over the past years, applications of NLP algorithms or systems were developed to automatically extract clinical information from free-text clinical notes [11-13]. Rule-based or machine learning-based NLP studies [6,14-22] have attempted to extract information on valve severity and related measurements from echocardiography reports. Most of these studies concentrated on extracting some specific conditions and measurements, such as aortic stenosis and peak velocity. Two exceptions are Nath et al. who created EchoInfer, a system capable of extracting about a set of data elements (~80) reported in the echocardiography reports [18], and Dong et al., who developed an NLP system that extracts about 43 data elements described in the echocardiography reports [19]. Although both systems extracted elements relevant to VHD, the performance was based on the overall data elements rather than the clinically relevant feature of the severity of individual VHD. Additionally, the small training and validation samples in both studies limited the capabilities to accurately assess performance for less common valve diseases like mitral, tricuspid, and pulmonic stenosis. The purpose of the current study is two folds: 1) develop and validate a computerized algorithm for extracting the severity of stenosis and regurgitation of the four heart valves: aortic valve, mitral valve, tricuspid valve, and pulmonic valve; and 2) apply the validated algorithms to all echocardiography reports within a large integrated health system, Kaiser Permanente Southern California (KPSC) to estimate the frequencies of VHD across a diverse population.

Methods

Study setting and population

The study subjects were health plan enrollees of KPSC, an integrated healthcare system providing comprehensive medical services to 4.8 million members across 15 large medical centers and 250+ medical offices throughout Southern California. The demographic characteristics of KPSC members are diverse and largely representative of the residents in Southern California [23] with health insurance through group plans, individual plans, Medicare, and Medicaid programs. Patients aged 18 or older who underwent at least one TTE within the KPSC system between January 1, 2011, and December 31, 2022, were included in this study.

The study protocol was reviewed and approved by the KPSC Institutional Review Board with a waiver of the requirement for informed consent. The steps for identifying stenosis and regurgitation are outlined in Figure 1, and detailed descriptions are as follows.

Echocardiography report extraction and annotation

The TTE reports during the study period were extracted from KPSC's EHR systems. These reports were written by physicians and were generally structured in a templated format. Most reports contain the following sections: 1) Title, patient demographics, performed procedure, performing provider, and procedure indication; 2) Exam quality; 3) Dimensions/ measurements; 4) Findings/results; 5) Impression; 6) Miscellaneous; 7) Summary/Conclusion; and 8) Physician signature. Despite the templated structure, the content within each section is in free-text format and the report could have varying order or incompleteness sections. Examples of deidentified TTE reports included in eTable 1.

An initial list of phrases and terms related to capture stenosis, regurgitation, and severity of the four heart valves was compiled based on the input of the study cardiologist (ML), published case definitions and ontologies [6,18-19, 24], and enriched by the training dataset to capture additional linguistic variations such as abbreviations and misspellings. The collected terms are listed in eTable 2.

To effectively capture the severity of the rare heart valve stenosis described in TTE reports, two sets of TTE reports were prepared for annotation and algorithm training. The first dataset contained a total of eight hundred TTE reports in which 200 reports were randomly selected from each of the four aortic valve peak velocity groups (≤ 2.5 m/s, 2.6-2.9 m/s, 3.0-4.0 m/s, ≥4.0 m/s) instead of simple random selection from the extracted entire TTE reports

(Dataset 1) . The second dataset contained another sample with 400 TTE reports based on diagnosis codes (Dataset 2): 134 reports randomly selected from patients with mitral stenosis diagnosis (International Classification of Diseases (ICD)-10 code: I05.0 or I05.2), 133 reports randomly selected from patients with tricuspid stenosis diagnosis (ICD-10: I07.0, I07.2, I36.0 or I36.2), and 133 randomly selected from patients with pulmonic stenosis diagnosis (ICD-10: I37.0 or I37.2). Both datasets were manually reviewed by an experienced board-certified cardiologist (ML) and a medical student (SA) to record the presence/absence (eTable 2) and severity (eTable 3) of stenosis and regurgitation of the four heart valves. These annotated TTE reports were split into 6 batches and each batch contained 200 reports. The first batch was reviewed by both annotators to ensure quality and consistency. The rest were equally split between the two annotators.

NLP Algorithm

we first divided the reports in the annotated datasets into these sections described in the above section of echocardiography report extraction and annotation, and then sub-sections based on the titles and subtitles. Each sub-section uniquely captures information on a specific valve (aortic, mitral, tricuspid, or pulmonic valve). The selected sections and sub-sections were then preprocessed through the letter lowercase conversion, misspelled word correction (as shown in eTable 4 obtained by the deep learning word2vec tool [25]), and tokenization (i.e., segmenting text into linguistic units such as words and punctuations) [26] for further NLP processing. 100% of Dataset 1 and 50% of Dataset 2 were used for training and 50% of Dataset 2 was used for validation.

We used the annotated reports to develop a rule-based computerized algorithm via an iterative process to determine the presence/absence and severity status of stenosis and regurgitation in the four heart valves (aortic, mitral, tricuspid, and pulmonic). eTable 5 summarized the included sections and the sub-sections from which the following search steps were applied. The process below was applied to each sentence within the included sections or subsections.

1) Search for terms associated with stenosis and regurgitation (eTable 1). If no relevant term was found, the status was labeled as “no evidence”.
2) If a relevant term is found, search for the negated terms associated with the identified stenosis and regurgitation terms. If a negation was found (e.g., no aortic stenosis, without evidence of aortic stenosis). The identified stenosis or regurgitation term was ignored.
3) Search for history terms in (eTable 6) (e.g., prior study showed trace mitral regurgitation) associated with the identified stenosis and regurgitation terms. If an associated history term was detected, the detected stenosis and regurgitation term was also ignored.
4) Search for severity terms (eTable 2). If no severity term was found, the sentence was labeled “unknown severity”. If multiple severity terms were detected, the severity of the report was assigned based on the following priority: prosthetic, very severe, severe, moderate to severe, moderate, mild to moderate, mild, trace to mild, trace, and sclerosis. Trace to mild and trace were only applied for regurgitation while sclerosis was only applied for aortic stenosis.

The discordant cases between the computerized algorithm and manually annotated labels were reviewed and adjudicated by an experienced cardiologist (ML). The adjudicated results were used to refine the algorithm and process if they were different from the computerized results within each round.

The results from the final computerized algorithm were compared with the manually annotated results in the validation dataset. The proportions of true positive (TP), false positive (FP), and false negative (FN) cases were used to estimate sensitivity, positive predicted value (PPV), and the overall F1-score (a measure of overall model fit). Sensitivity was defined as the proportion of reports correctly labeled by the computerized algorithm (TP) among all reports (TP+FN) ascertained by chart review. PPV was defined as the proportion of reports correctly labeled (TP) among all those labeled by the computerized algorithm (TP+FP). The overall accuracy F1-score for each comparison was calculated via the standard formula 2xPPVxsensitivity/(PPV+sensitivity).

Estimating the severity of stenosis and regurgitation at report level

The finalized computerized algorithm was implemented via Python 3.10 to process the entire study set of TTE reports. The status and severity level of stenosis and regurgitation for each of the four heart valves (aortic, mitral, tricuspid, and pulmonic) were reported for all TTE reports during the study period. In TTE reports with detected heart valve diseases, the severity levels of these valve conditions at report level were summarized by age group (18-49, 50-64, 65-79, 80+ years of age), sex, and race/ethnicity (non-Hispanic white, non-Hispanic black, non-Hispanic Asian/Pacific islanders, non-Hispanic Native American, Hispanic, multiple races, other/unknown).

Results

Performance assessment of NLP algorithm

The performance of the computerized algorithm against the manually annotated results based on the validation dataset is summarized in Table 1. The PPV, sensitivity, and F1-score of having positive stenosis and regurgitation were 100.0%, 100.0%, and 1.00 for aortic, mitral, and tricuspid valves, 96.2%, 96.2%, and 0.96 for pulmonic stenosis, and

97.0%, 98.5% and 0.98 for pulmonic regurgitation, respectively. The PPV, sensitivity, and F1-score of prosthetic valves were also 100.0%, 100%, and 1.00 for aortic, mitral, and tricuspid valves, and 92.3%, 92.3%, and 0.92 for pulmonic valves, respectively. For TTEs with specific severity detected, the PPV was 100.0% for most of the severity categories with several exceptions (e.g., 80.0% for severe mitral stenosis and 50.0% for unknown severity pulmonic stenosis, Table 1). The sensitivity was also 100.0% for most of the severity categories with several exceptions (e.g., 87.5% for moderate to severe mitral stenosis, Table 1).

Estimating the severity of stenosis and regurgitation at report level

A total of 1,225,270 TTE reports among 677,106 patients were extracted from the KPSC EHR system during the study period. Slightly more than half (50.7%, data not shown) of them were performed on males. The median age at the time of echocardiogram was 67 years (IQR=[55, 77]). The mean number of performed TTEs per patient was 1.8 (SD=1.6) during the study period (data not shown). Table 2 summarizes the distribution of the stenosis and regurgitation severity across the TTE reports. Of the 1,225,270 TTE reports, 111,300 (9.1%), 20,246 (1.7%), 397 (0.03%), 2,585 (0.2%), 345,115 (28.2%), 802,103 (65.5%), 903,965 (73.8%), and 286,903 (23.4%) reports had evidence of aortic stenosis, mitral stenosis, tricuspid stenosis, pulmonic stenosis, aortic regurgitation, mitral regurgitation, tricuspid regurgitation, and pulmonic regurgitation, respectively. In addition, 50,507 (4.1%), 22,656 (1.9%), 1,685 (0.1%), and 1,767 (0.1%) of the heart valves were identified as the prosthetic aortic valve, mitral valve, tricuspid valve, and pulmonic valve, respectively.

In TTE reports with detected heart valve diseases, the severity level of these valve conditions stratified by gender, race/ethnicity, and age group at the time of the TTE are presented in Table 3. Males had a higher frequency of aortic stenosis and all four valvular regurgitations while females had more mitral stenosis, tricuspid stenosis, and pulmonic stenosis. Non-Hispanic whites had the highest frequency among all four valvular stenosis and regurgitations. The distribution of stenosis and regurgitation severity was similar across the race/ethnicity group. The frequencies of aortic and mitral stenosis were increased with age whereas the frequencies of tricuspid and pulmonic stenosis were decreased with age. The frequency of valvular regurgitation was increased by age for all four heart valves. Among the TTEs with detected stenosis, younger patients were more likely to have mild aortic stenosis, while older patients were more likely to have severe ones. However, the frequencies of mitral stenosis were in the opposite direction (more mild mitral stenosis for older patients and more severe mitral stenosis for younger patients). In contrast, for the TTEs with detected regurgitation, the younger patients had a higher frequency of severe/very severe aortic regurgitation, while older patients had higher frequencies of mild valve regurgitation and severe/very severe mitral/tricuspid regurgitation.

Discussions

In this study, we developed a computerized algorithm to identify the presence/absence and the severity of stenosis and regurgitation of the four heart valves from reports of routinely performed TTEs. This algorithm yielded high accuracy in extracting information except for a few severity groups due to their small numbers. This process was successfully implemented in a large integrated healthcare system to estimate the frequencies of VHD described in the TTE reports among a diverse population.

Echocardiography is the primary imaging technique for evaluating the severity of heart valve disease. Incorporating a developed NLP algorithm to extract information on valve lesion severity from unstructured echocardiogram reports allows identification of patients with valve disease across a large population. This is useful because the frequency of surveillance imaging is dependent on the severity of the valve lesion. Specifically, patients with mild valve lesion typically require imaging every 3-5 years, those with moderate lesion every 1-2 years, and patients with severe lesions need evaluations every 6-12 months [27]. By identifying and categorizing patients with valve disease at a population level, this ensures that all patients receive timely and adequate follow-up.

The performance of the algorithms reported in the current study was comparable with those reported in previous studies [6,18-19]. In line with findings from previous studies [6,18-19], we also observed the percentage of valvular heart disease increased with patient age [9]. Valvular heart disease affected both genders, although certain conditions showed gender-specific patterns. Aortic regurgitation was more commonly observed in males, a finding that aligns with other studies indicating a male predominance of aortic regurgitation [28]. Conversely, tricuspid regurgitation was more commonly observed in women in this population. Further research into the incidence, prevalence, and associated risk factors of these valve lesions will enhance our understanding of the causes behind the observed gender differences [29].

Recent studies have attempted to extract stenosis and regurgitation from echocardiography reports [6,17-19]. The study by Solomon et al. [6] only focused primarily on the extraction of aortic stenosis and few continuous measurements. Although the studies by Nath et al. [18] and Dong et al. [19] attempted to retrieve stenosis and regurgitation of heart valves, their performance were not assessed for each condition independently, and neither of the authors evaluated performance by severity group. Even for the combined evaluation, the study by Dong et al. [19] reported a low performance for both precision and recall of identifying stenosis of the four hear valves. The approach taken by the current study has several advantages. First, part of our training and validation samples included TTE reports of potential patients diagnosed with mitral stenosis, tricuspid stenosis, and pulmonic stenosis. Therefore, the samples included a fair number of patients with these rare conditions, which allowed the computerized algorithm to train/recognize the corresponding potential patterns. Second, our study evaluated each case of stenosis or regurgitation independently. However, the performance of some severity levels needs cautious interpretation due to few cases and small validation samples. A large sample can yield more robust performance in the future work. In addition to extracting the severity, future work can also enhance the computerized algorithm to extract other VHD related measurements [19] to facilitate patient care and management.

Research of heart valve conditions based on diagnosis codes only may be impacted by the inaccuracy of coding, especially for minority populations. Crousillat et al. study [7] showed that diagnosis codes for aortic stenosis are less accurate for racial and ethnic minorities and less severe stages of the disease and therefore cannot be used to evaluate observed care disparities. This issue is likely to be alleviated by the application of NLP on TTE reports. Solomon et al. study [6] demonstrated that the NLP application captured 35.4% more aortic stenosis compared to diagnosis code identification. Future studies are needed to understand and mitigate recently identified VHD care disparities and improve outcomes for patients [28].

Advanced transformer language models, including bidirectional encoder representations from transformers [30], have gained popularity in research involving NLP. These large language models can effectively understand the meaning of context and capture the intricate relationships within the text via embedding representation. They have been widely used for analyzing information from unstructured notes in the health care domain [31, 32]. Research in this area in future work is warranted to further boost the performance of VHD severity level via the rule-based approach.

Our study acknowledged several limitations. First, the completeness and accuracy of the extracted information were dependent on the information documented in the TTE reports. Incomplete or inaccurate documentation could lead to misclassification. Despite our efforts to correct misspelled words, there could be additional unidentified errors. Second, although our training process was quite comprehensive and included a relatively large number of notes, the rules, and lexicons developed from our training datasets were still not highly comprehensive.

For example, the severity of mitral stenosis in “Moderate to borderline severe calcific mitral stenosis” should be “moderate to severe”, however, the current algorithm identified it as “severe” because of the additional word “borderline” prior to the “severe”. Therefore, more samples could be used to enhance the rule and lexicons in the future, especially for rare conditions (mitral, tricuspid, and pulmonic stenosis). Third, numerous abbreviations of the study used terms with multiple meanings complicated the identification process. For instance, the word “as” could mean “aortic stenosis”, “ms” could mean “mitral stenosis” or millisecond, a time unit used for velocity measurements, and “tr” could mean “trace” or “tricuspid regurgitation”. Although we have applied a set of rules to determine the exclusion of used abbreviated terms, the algorithm could still potentially misuse the meaning of the abbreviation of these terms. Fourth, if a severity term was found to appear prior to a set of listed together stenosis or regurgitation terms (such as mild as/ai/mr), our current algorithm only assigned the severity to the first term leading to incomplete labeling of severity of other terms. Last, the TTE reports for patients with congenital valve conditions frequently used the terms “systemic AV” and “subpulmonic AV”, which represented the morphologic tricuspid valve and morphologic mitral valve, respectively, However, the meanings of these two terms are different in non-congenital patients. Our current algorithm did not search for these two terms for congenital patients, which could lead to potential misclassification of congenital valvular conditions.

Conclusion

The developed computerized algorithm can effectively identify the heart valve’s stenosis and regurgitation and the severity of valvular involvement. This algorithm has potential applications in clinical research and patient cardiovascular care management. The developed computerized algorithm may require modifications due to variations in the format and presentation of TTE reports when it is applied to other healthcare organizations.

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Abbreviations
EHR: electronic health record
FN: false negative
FP: false positive
ICD: International Classification of Diseases
KPSC: Kaiser Permanente Southern California
NLP: natural language processing
PPV: positive predictive value
VHD: valvular heart disease
TN: true negative
TP: true positive
TTE: transthoracic echocardiogram

Table 1. The computerized algorithm performance against the adjudicated chart review results for the 200 TTE reports in the validation dataset.

Severity Status	Stenosis						Regurgitation					
	TP	FP	FN	PPV(%)	Sensitivity(%)	F1-score	TP	FP	FN	PPV(%)	Sensitivity(%)	F1-score
Aortic Valve												
No/no evidence	113	0	1	100.0	99.1	1.00	109	0	0	100.0	100.0	1.00
Prosthetic	28	0	0	100.0	100.0	1.00	28	0	0	100.0	100.0	1.00
Sclerosis	28	1	0	96.6	100.0	0.98	0	0	0	-	-	-
Severity detected	31	0	0	100.0	100.0	1.00	63	0	0	100.0	100.0	1.00
Trace	0	0	0	-	-	-	26	0	0	100.0	100.0	1.00
Trace to mild	0	0	0	-	-	-	0	0	0	100.0	100.0	1.00
Mild	15	0	0	100.0	100.0	1.00	23	0	0	100.0	100.0	1.00
Mild to moderate	1	0	0	100.0	100.0	1.00	7	0	0	100.0	100.0	1.00
Moderate	8	0	0	100.0	100.0	1.00	5	0	0	100.0	100.0	1.00
Moderate to severe	0	0	0	100.0	100.0	1.00	1	0	0	100.0	100.0	1.00
Severe	7	0	0	100.0	100.0	1.00	1	0	0	100.0	100.0	1.00
Very severe	0	0	0	-	-	-	0	0	0	-	-	-
Unknown severity	0	0	0	-	-	-	0	0	0	-	-	-
Mitral Valve												
No/no evidence	135	0	0	100.0	100.0	1.00	60	0	0	100.0	100.0	1.00
Prosthetic	17	0	0	100.0	100.0	1.00	17	0	0	100.0	100.0	1.00
Severity detected	48	0	0	100.0	100.0	1.00	123	0	0	100.0	100.0	1.00
Trace	0	0	0	-	-	-	47	0	0	100.0	100.0	1.00
Trace to mild	0	0	0	-	-	-	2	0	1	100.0	66.7	0.80
Mild	7	0	0	100.0	100.0	1.00	35	1	0	97.2	100.0	0.99
Mild to moderate	7	0	0	100.0	100.0	1.00	15	0	0	100.0	100.0	1.00
Moderate	21	0	0	100.0	100.0	1.00	13	0	1	100.0	92.9	0.96
Moderate to severe	7	0	1	100.0	87.5	0.93	3	0	0	100.0	100.0	1.00
Severe	4	1	0	80.0	100.0	0.89	5	1	0	83.3	100.0	0.91
Very severe	0	0	0	-	-	-	0	0	0	-	-	-
Unknown severity	1	0	0	100.0	100.0	1.00	0	0	0	-	-	-
Tricuspid Valve												
No/no evidence	185	0	0	100.0	100.0	1.00	41	0	0	100.0	100.0	1.00
Prosthetic	10	0	0	100.0	100.0	1.00	10	0	0	100.0	100.0	1.00
Severity detected	5	0	0	100.0	100.0	1.00	149	0	0	100.0	100.0	1.00
Trace	0	0	0	-	-		46	0	1	100.0	97.9	0.99

Trace to mild	0	0	0	-	-		2	1	0	66.7	100.0	0.80
Mild	1	0	0	100.0	100.0	1.00	43	0	0	100.0	100.0	1.00
Mild to moderate	0	0	0	-	-		22	0	0	100.0	100.0	1.00
Moderate	1	0	0	100.0	100.0	1.00	19	0	0	100.0	100.0	1.00
Moderate to severe	2	0	0	100.0	100.0	1.00	5	0	1	100.0	83.3	0.91
Severe	0	0	0	-	-	-	10	1	0	90.9	100.0	0.95
Very severe	0	0	0	-	-	-	0	0	0	-	-	-
Unknown severity	1	0	0	100.0	100.0	1.00	0	0	0	-	-	-
Pulmonic Valve												
No/no evidence	159	2	2	98.8	98.8	0.99	121	0	1	100.0	99.2	1.00
Prosthetic	12	1	1	92.3	92.3	0.92	12	1	1	92.3	92.3	0.92
Severity detected	25	1	1	96.2	96.2	0.96	64	2	1	97.0	98.5	0.98
Trace	0	0	0	-	-	-	24	0	1	100.0	96.0	0.98
Trace to mild	0	0	0	-	-	-	0	0	0	-	-	-
Mild	18	0	1	100.0	94.7		28	1	0	96.6	100.0	0.98
Mild to moderate	4	0	0	100.0	100.0	1.00	3	0	0	100.0	100.0	1.00
Moderate	1	0	0	100.0	100.0	1.00	6	0	0	100.0	100.0	1.00
Moderate to severe	0	0	0	-	-	-	1	0	0	100.0	100.0	1.00
Severe	1	0	0	100.0	100.0	1.00	2	1	0	66.7	100.0	0.80
Very severe	1	0	0	100.0	100.0	1.00	0	0	0	-	-	-
Unknown severity	2	1	0	50.0	100.0	0.67	0	0	0	-	-	-

TTE: Transthoracic echocardiogram; PPV: positive predicted value.
TP: Both computerized algorithm and chart review had the same result; FP: computerized algorithm identified as yes, but chart review labeled as no; FN: chart review labeled as yes, but computerized algorithm identified as no.

Table 2. Detection frequency and severity of stenosis and regurgitation by valve disease based on 1,225,270 TTE reports performed in the KPSC setting during 2011-2022. Reported as N (column %).

Conditions detected in TTE reports (n,%)	Stenosis				Regurgitation			
	Aortic valve	Mitral valve	Tricuspid valve	Pulmonic valve	Aortic valve	Mitral valve	Tricuspid valve	Pulmonic valve
Prosthetic	50507 (4.1)	22656 (1.8)	1685 (0.1)	1767 (0.1)	50507 (4.1)	22656 (1.8)	1685 (0.1)	1767 (0.2)
Sclerosis	286784 (23.4)	-	-	-	-	-	-	-
No/no evidence	776679 (63.4)	1182368 (96.5)	1223188 (98.8)	1220918 (99.6)	829648 (67.7)	400511 (32.7)	319620 (6.1)	936600 (76.4)
Valve disease detected¶	111300 (9.1)	20246 (1.7)	397 (0.1)	2585 (0.2)	345115 (28.2)	802103 (65.5)	903965 (73.8)	286903 (23.4)
Trace	-	-	-	-	133423 (38.7)	367737 (45.9)	439725 (48.6)	199346 (69.5)
Trace to mild	-	-	-	-	8371 (2.4)	20178 (2.5)	22022 (2.4)	4887 (1.7)
Mild	49845 (44.8)	11078 (54.7)	196 (49.4)	1758 (68.0)	146202 (42.4)	280238 (34.9)	309498 (34.2)	71097 (24.8)
Mild to moderate	9125 (8.2)	2183 (10.8)	67 (16.9)	160 (6.2)	27019 (7.8)	52957 (6.6)	46834 (5.2)	5287 (1.8)
Moderate	24517 (22.0)	3995 (19.7)	45 (11.3)	301 (11.6)	22912 (6.6)	51847 (6.5)	57429 (6.4)	4998 (1.7)
Moderate to severe	7615 (6.8)	901 (4.5)	11 (2.8)	38 (1.5)	3756 (1.1)	15813 (2.0)	15219 (1.7)	444 (0.2)
Severe	17091 (15.4)	1216 (6.0)	24 (6.1)	66 (2.6)	2624 (0.8)	11906 (1.5)	12512 (1.4)	0 (0.0)
Very severe	1199 (1.1)	11 (0.1)	0 (0.0)	4 (0.2)	13 (0.0)	34 (0.0)	0 (0.0)	0 (0.0)
Unknown severity	1908 (1.7)	862 (4.3)	54 (13.6)	258 (10.0)	795 (0.2)	1393 (0.2)	698 (0.1)	282 (0.1)

TTE: Transthoracic echocardiogram
KPSC: Kaiser Permanente Southern California
¶ percentage among the severity group

Table 3. The severity of stenosis and regurgitation captured in the 1,225,270 TTE reports performed at KPSC during 2011-2022 by valve disease, gender, race/ethnicity, and age at the TTE performed time. Reported as N (row %).

	Severity of detected heart valve disease									
	Trace	**Trace to mild**	**Mild**	**Mild to moderate**	**Moderate**	**Moderate to severe**	**Severe**	**Very severe**	**Unknown severity**	**All**
Aortic stenosis										
Gender										
Female	-	-	23784 (46.8)	4088 (8.0)	10739 (21.1)	3228 (6.4)	7461 (14.7)	671 (1.3)	887 (1.7)	50858
Male	-	-	26061 (43.1)	5037 (8.3)	13777 (22.8)	4386 (7.3)	9640 (15.9)	528 (0.9)	1021 (1.7)	60440
Age group										
18-49	-	-	1581 (51.3)	216 (7.0)	718 (23.3)	120 (3.9)	287 (9.3)	15 (0.5)	147 (4.8)	3084
50-64	-	-	6206 (48.1)	934 (7.2)	2659 (20.6)	708 (5.5)	1955 (15.2)	143 (1.1)	290 (2.3)	12895
65-79	-	-	23690 (46.9)	4165 (8.2)	11004 (21.8)	3251 (6.4)	7678 (17.2)	464 (0.9)	803 (1.6)	50548
80+	-	-	18368 (41.0)	3810 (8.5)	10136 (22.6)	3536 (7.9)	7678 (17.2)	577 (1.3)	668 (1.5)	44773
Race/ethnicity										
Non-Hispanic white	-	-	28652 (43.3)	5387 (8.2)	14816 (22.4)	4796 (7.3)	10731 (16.2)	712 (1.1)	1019 (1.5)	66113
Non-Hispanic black	-	-	4174 (47.7)	743 (8.5)	1922 (22.0)	551 (6.3)	1116 (12.8)	81 (0.9)	167 (1.9)	8754
Hispanic	-	-	11868 (45.0)	2140 (8.1)	5728 (21.7)	1724 (6.5)	4043 (15.3)	333 (1.3)	533 (2.0)	26368
Non-Hispanic Asian/pacific islander	-	-	4560 (52.0)	763 (8.7)	1738 (19.8)	490 (5.6)	1006 (11.5)	59 (0.7)	167 (1.9)	8783
Non-Hispanic Native American	-	-	97 (44.3)	19 (8.7)	44 (20.1)	8 (3.7)	42 (19.2)	4 (1.8)	5 (2.3)	219
Multiple	-	-	61 (43.6)	10 (7.1)	38 (27.1)	3 (2.1)	20 (14.3)	1 (0.7)	7 (5.0)	140
Other/Unknown	-	-	433 (46.9)	563 (6.8)	231 (25.0)	43 (4.7)	133 (14.4)	10 (1.1)	10 (1.1)	923
Aortic regurgitation										
Gender										
Female	61858 (38.7)	3899 (2.4)	67754 (42.3)	13225 (8.3)	10776 (6.7)	1383 (0.9)	739 (0.5)	7 (0.0)	387 (0.2)	160028
Male	71564 (38.7)	4472 (2.4)	78448 (42.4)	13794 (7.5)	12134 (6.6)	2373 (1.3)	1885 (1.0)	6 (0.0)	408 (0.2)	185084
Age group										
18-49	12257 (50.84)	726 (3.01)	6734 (27.9)	1516 (6.3)	1608 (6.7)	525 (2.2)	611 (2.5)	1 (0.0)	131 (0.5)	24109
50-64	29362 (47.3)	1589 (2.6)	22000 (35.4)	3727 (6.0)	3648 (5.9)	851 (1.4)	789 (1.3)	2 (0.0)	179 (0.3)	62147
65-79	60783 (38.8)	3956 (2.5)	67482 (43.0)	12096 (7.7)	9834 (6.3)	1495 (1.0)	846 (0.5)	7 (0.0)	331 (0.2)	156830
80+	31021 (30.4)	2100 (2.1)	49986 (49.0)	9680 (9.5)	7822 (7.7)	885 (0.9)	378 (0.4)	3 (0.0)	154 (0.2)	102029
Race/ethnicity										
Non-Hispanic white	66754 (38.2)	4229 (2.4)	75308 (43.1)	13994 (8.0)	11261 (6.5)	1724 (1.0)	1079 (0.6)	4 (0.0)	339 (0.2)	174692
Non-Hispanic black	14550 (39.3)	777 (2.1)	15254 (41.2)	2751 (7.4)	2806 (7.6)	485 (1.3)	348 (0.9)	1 (0.0)	75 (0.2)	37047
Hispanic	35341 (41.1)	2211 (2.6)	34877 (40.5)	2751 (7.4)	5422 (6.3)	971 (1.1)	791 (0.9)	7 (0.0)	253 (0.3)	86046
Non-Hispanic Asian/pacific islander	14852 (34.8)	1045 (2.5)	18844 (44.2)	3768 (8.8)	3147 (7.4)	522 (1.2)	361 (0.9)	1 (0.0)	117 (0.3)	42657
Non-Hispanic Native American	257 (41.5)	14 (2.3)	240 (38.71)	53 (8.9)	47 (7.6)	6 (1.0)	3 (0.5)	0 (0.0)	0 (0.0)	620
Multiple	242 (45.2)	8 (1.5)	202 (37.8)	38 (7.1)	26 (4.9)	11 (2.1)	6 (1.1)	0 (0.0)	2 (0.4)	535
Other/Unknown	1427 (40.6)	87 (2.5)	1477 (42.0)	242 (6.9)	203 (5.8)	37 (1.1)	36 (1.0)	0 (0.0)	9 (0.3)	3518

Mitral stenosis										
Gender										
Female	-	-	7536 (53.3)	1562 (11.1)	2850 (20.2)	675 (4.8)	923 (6.5)	6 (0.0)	579 (4.1)	14130
Male	-	-	3542 (57.9)	621 (10.2)	1145 (18.7)	226 (3.7)	293 (4.8)	5 (0.1)	284 (4.6)	6116
Age group										
18-49	-	-	399 (41.1)	115 (11.8)	205 (21.1)	70 (7.2)	106 (10.9)	1 (0.1)	75 (7.7)	971
50-64	-	-	1235 (45.3)	271 (9.9)	643 (23.6)	164 (6.0)	269 (9.9)	1 (0.0)	145 (5.3)	2728
65-79	-	-	4727 (54.8)	945 (11.0)	1687 (19.5)	390 (4.5)	521 (6.0)	6 (0.1)	356 (4.1)	8632
80+	-	-	4717 (59.6)	852 (10.8)	1460 (18.5)	277 (3.5)	320 (4.0)	3 (0.0)	286 (3.6)	7915
Race/ethnicity										
Non-Hispanic white	-	-	5969 (58.2)	1090 (10.6)	1965 (19.2)	395 (3.9)	464 (4.5)	3 (0.0)	375 (3.7)	10261
Non-Hispanic black	-	-	937 (54.3)	202 (11.7)	304 (17.6)	72 (4.4)	123 (7.1)	1 (0.1)	84 (4.9)	1725
Hispanic	-	-	3014 (52.0)	638 (11.0)	1168 (20.1)	272 (4.7)	413 (7.1)	3 (0.1)	293 (5.1)	5801
Non-Hispanic Asian/pacific islander	-	-	1047 (46.2)	239 (10.5)	522 (23.0)	154 (6.8)	202 (8.9)	2 (0.1)	102 (4.5)	2268
Non-Hispanic Native American	-	-	18 (51.4)	2 (5.7)	9 (25.7)	0 (0.0)	4 (11.4)	0 (0.0)	2 (5.7)	35
Multiple	-	-	20 (71.4)	1 (3.6)	4 (14.3)	2 (7.1)	0 (0.0)	0 (0.0)	1 (3.6)	28
Other/Unknown	-	-	73 (57.0)	12 (9.4)	23 (18.0)	3 (2.3)	10 (7.8)	2 (1.6)	5 (3.9)	128
Mitral regurgitation										
Gender										
Female	182678 (45.7)	10228 (2.6)	138467 (34.7)	27448 (6.9)	26641 (6.7)	7985 (2.0)	5504 (1.4)	15 (0.0)	613 (0.2)	399579
Male	185049 (46.0)	9950 (49.3)	141765 (35.2)	25509 (6.3)	25205 (6.3)	7828 (1.9)	6402 (1.6)	19 (0.0)	780 (0.2)	402507
Age group										
18-49	76721 (68.1)	3265 (2.9)	24458 (21.7)	2999 (2.7)	2917 (2.6)	1050 (0.9)	1075 (1.0)	7 (0.0)	162 (0.1)	112654
50-64	103920 (54.4)	5358 (2.8)	59059 (30.9)	8725 (4.6)	8367 (4.4)	2728 (1.4)	2541 (1.3)	5 (0.0)	328 (0.2)	191031
65-79	138927 (42.2)	8388 (2.6)	124236 (37.7)	23637 (7.2)	22160 (6.7)	6619 (2.0)	4971 (1.5)	11 (0.0)	608 (0.2)	329557
80+	48169 (28.5)	3167 (1.9)	72485 (42.9)	17596 (10.4)	18403 (10.9)	5416 (3.2)	3319 (2.0)	11 (0.0)	295 (0.2)	168861
Race/ethnicity										
Non-Hispanic white	175195 (44.1)	10197 (2.6)	141813 (35.7)	28286 (7.1)	26886 (6.8)	8294 (2.1)	6045 (1.5)	12 (0.0)	653 (0.2)	397381
Non-Hispanic black	38542 (41.9)	2081 (2.3)	34013 (37.0)	6052 (6.6)	7220 (7.9)	2184 (2.4)	1742 (1.9)	4 (0.0)	166 (0.2)	92004
Hispanic	108152 (50.8)	5485 (2.6)	69505 (32.7)	11801 (5.5)	11544 (5.4)	3405 (1.6)	2633 (1.2)	15 (0.0)	353 (0.2)	212893
Non-Hispanic Asian/pacific islander	38774 (44.6)	2063 (2.4)	31043 (35.7)	6196 (7.1)	5641 (6.5)	1750 (2.0)	1310 (1.5)	3 (0.0)	198 (0.2)	86978
Non-Hispanic Native American	809 (48.9)	38 (2.3)	557 (33.7)	94 (5.7)	101 (6.1)	26 (1.6)	24 (1.5)	0 (0.0)	4 (0.2)	1653
Multiple	847 (51.5)	54 (3.3)	487 (29.2)	98 (6.0)	95 (5.8)	37 (2.3)	30 (1.8)	0 (0.0)	4 (0.2)	1646
Other/Unknown	5418 (56.7)	260 (2.7)	2826 (29.6)	430 (4.5)	360 (3.8)	117 (1.2)	122 (1.3)	0 (0.0)	15 (0.2)	9548
Tricuspid stenosis										
Gender										
Female	-	-	118 (52.4)	38 (16.9)	24 (10.7)	4 (1.8)	11 (4.9)	0 (0.0)	30 (13.3)	225
Male	-	-	78 (45.35)	29 (16.9)	21 (12.2)	7 (4.1)	13 (7.6)	0 (0.0)	24 (14.0)	172
Age group										
18-49	-	-	62 (47.3)	50 (38.2)	4 (3.1)	1 (0.8)	4 (3.1)	0 (0.0)	10 (7.6)	131

50-64	-	-	35 (49.3)	5 (7.0)	9 (12.7)	3 (4.2)	11 (15.5)	0 (0.0)	8 (11.3)	71
65-79	-	-	69 (55.7)	5 (4.0)	21 (16.9)	4 (3.2)	5 (4.0)	0 (0.0)	20 (16.1)	124
80+	-	-	30 (42.3)	7 (9.9)	11 (15.5)	3 (4.2)	4 (5.6)	0 (0.0)	16 (22.5)	71
Race/ethnicity										
Non-Hispanic white	-	-	83 (49.1)	33 (19.5)	17 (10.1)	6 (3.6)	9 (5.3)	0 (0.0)	21 (12.4)	169
Non-Hispanic black	-	-	24 (49.0)	14 (28.6)	4 (8.2)	0 (0.0)	4 (8.2)	0 (0.0)	3 (6.1)	49
Hispanic	-	-	67 (49.3)	20 (14.7)	20 (14.7)	4 (2.9)	8 (5.9)	0 (0.0)	17 (12.5)	136
Non-Hispanic Asian/pacific islander	-	-	19 (50.0)	0 (0.0)	3 (7.9)	1 (2.6)	3 (7.9)	0 (0.0)	12 (31.6)	38
Non-Hispanic Native American	-	-	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	1 (100.0)	1
Multiple	-	-	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0
Other/Unknown	-	-	3 (75.0)	0 (0.0)	1 (25.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	4
Tricuspid regurgitation										
Gender										
Female	210902 (45.8)	11301 (2.5)	159471 (34.7)	26692 (5.8)	33787 (7.3)	9467 (2.1)	8112 (1.8)	19 (0.0)	339 (0.1)	460090
Male	228812 (51.6)	10721 (2.4)	150020 (33.8)	20141 (4.5)	23641 (5.3)	5752 (1.3)	4400 (1.0)	9 (0.0)	359 (0.1)	621237
Age group										
18-49	92627 (65.7)	4466 (3.2)	35576 (25.3)	3246 (2.3)	3218 (2.3)	829 (0.6)	807 (0.6)	4 (0.0)	130 (0.1)	140903
50-64	123678 (57.7)	5913 (2.8	65928 (30.8)	7364 (3.4)	7716 (3.6)	1916 (0.9)	1694 (0.8)	4 (0.0)	175 (0.1)	214388
65-79	167337 (45.8)	8545 (2.3)	134515 (36.8)	20333 (5.6)	23740 (6.5)	5915 (1.6)	4840 (1.3)	9 (0.0)	286 (0.1)	365520
80+	56083 (30.6)	3098 (1.7)	73479 (40.1)	15891 (8.7)	22755 (12.4)	6559 (3.6)	5171 (2.8)	11 (0.0)	107 (0.1)	183154
Race/ethnicity										
Non-Hispanic white	212581 (48.4)	11162 (2.5)	150831 (34.3)	23819 (5.4)	27795 (6.3)	7405 (1.7)	5429 (1.2)	9 (0.0)	314 (0.1)	439345
Non-Hispanic black	44579 (41.8)	2031 (1.9)	39499 (37.1)	6175 (5.8)	9208 (8.6)	2486 (2.3)	2449 (2.3)	0 (0.0)	119 (0.1)	106546
Hispanic	127913 (52.0)	6209 (2.5)	80737 (32.8)	10890 (4.4)	13464 (5.5)	3485 (1.4)	3156 (1.3)	11 (0.0)	186 (0.1)	24051
Non-Hispanic Asian/pacific islander	46213 (47.4)	2225 (2.3)	33997 (34.9)	5464 (5.6)	6430 (6.6)	1692 (1.7)	1354 (1.4)	8 (0.0)	71 (0.1)	97454
Non-Hispanic Native American	981 (53.7)	37 (2.0)	596 (32.6)	73 (4.0)	91 (5.0)	24 (1.3)	24 (1.3)	0 (0.0)	1 (0.1)	1827
Multiple	1016 (53.9)	67 (3.6)	584 (31.0)	74 (3.9)	93 (4.9)	20 (1.1)	29 (1.5)	0 (0.0)	1 (0.1)	1884
Other/Unknown	6442 (59.3)	291 (2.7)	3254 (30.0)	339 (3.1)	348 (3.2)	107 (1.0)	71 (0.7)	0 (0.0)	6 (0.1)	10858
Pulmonic stenosis										
Gender										
Female	-	-	979 (70.0)	84 (6.0)	166 (11.9)	24 (1.7)	24 (1.7)	4 (0.3)	118 (8.4)	1399
Male	-	-	779 (65.7)	76 (6.4)	134 (11.3)	14 (1.2)	42 (3.5)	0 (0.0)	140 (11.8)	1185
Age group										
18-49	-	-	1074 (67.5)	108 (6.8)	212 (13.3)	33 (2.1)	49 (3.1)	4 (0.3)	111 (7.0)	1591
50-64	-	-	325 (69.0)	31 (6.6)	55 (11.7)	3 (0.6)	8 (1.7)	0 (0.0)	49 (10.4)	471
65-79	-	-	258 (67.9)	15 (4.0)	26 (6.8)	2 (0.5)	2 (0.5)	0 (0.0)	77 (20.3)	380
80+	-	-	101 (70.6)	6 (4.2)	8 (5.6)	0 (0.0)	7 (4.9)	0 (0.0)	21 (14.7)	143
Race/ethnicity										
Non-Hispanic white	-	-	680 (68.8)	62 (6.3)	92 (9.3)	12 (1.2)	25 (2.5)	2 (0.2)	115 (11.6)	988
Non-Hispanic black	-	-	123 (63.7)	11 (5.7)	23 (11.9)	6 (3.1)	3 (1.6)	0 (0.0)	27 (14.0)	192
Hispanic	-	-	770 (68.3)	66 (5.9)	147 (13.1)	10 (0.9)	33 (2.9)	1 (0.1)	95 (8.5)	1122

Non-Hispanic Asian/pacific islander	-	-	135 (64.9)	18 (8.7)	25 (12.0)	9 (4.3)	5 (2.40)	1 (0.5)	15 (7.2)	208
Non-Hispanic Native American	-	-	7 (100.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	7
Multiple	-	-	6 (50.0)	2 (16.7)	1 (8.3)	1 (8.3)	0 (0.0)	0 (0.0)	2 (16.7)	12
Other/Unknown	-	-	37 (67.3)	1 (1.8)	13 (23.6)	0 (0.0)	0 (0.0)	0 (0.0)	4 (7.3)	55
Pulmonic regurgitation										
Gender										
Female	97526 (69.9)	2436 (1.8)	33963 (24.3)	2550 (1.8)	2418 (1.7)	231 (0.2)	251 (0.2)	0 (0.00)	153 (0.1)	139528
Male	101816 (69.1)	2551 (1.7)	37134 (25.2)	2737 (1.9)	2580 (1.8)	211 (0.1)	211 (0.1)	0 (0.00)	129 (0.1)	147369
Age group										
18-49	36628 (77.7)	870 (1.8)	7991 (16.9)	583 (1.2)	607 (1.3)	127 (0.27)	294 (0.6)	0 (0.00)	71 (0.2)	47171
50-64	48999 (76.0)	1105 (1.7)	12745 (19.8)	706 (1.1)	699 (1.1)	84 (0.1)	71 (0.1)	0 (0.00)	67 (0.1)	64476
65-79	78082 (68.2)	2038 (1.8)	30005 (26.2)	2099 (1.8)	1923 (1.7)	127 (0.1)	70 (0.1)	0 (0.00)	107 (0.1)	114451
80+	35637 (58.6)	974 (1.6)	20356 (33.5)	1899 (3.1)	1769 (2.9)	106 (0.2)	27 (0.0)	0 (0.00)	37 (0.1)	60850
Race/ethnicity										
Non-Hispanic white	94375 (70.0)	2519 (1.9)	32871 (24.4)	2365 (1.8)	2139 (1.6)	175 (0.1)	184 (0.1)	0 (0.00)	110 (0.1)	134738
Non-Hispanic black	22062 (63.4)	541 (1.6)	10338 (29.7)	847 (2.4)	885 (2.5)	61 (0.2)	51 (0.2)	0 (0.00)	38 (0.1)	34823
Hispanic	55901 (72.3)	1332 (1.7)	17330 (22.4)	1190 (2.4)	1162 (1.5)	146 (0.2)	175 (0.2)	0 (0.00)	88 (0.1)	77324
Non-Hispanic Asian/pacific islander	23340 (66.4)	514 (1.5)	9567 (27.2)	824 (2.3)	767 (2.2)	55 (0.2)	46 (0.1)	0 (0.00)	40 (0.1)	35153
Non-Hispanic Native American	421 (70.6)	15 (2.5)	142 (23.8)	10 (1.7)	7 (1.2)	0 (0.0)	0 (0.0)	0 (0.00)	1 (0.2)	2025
Multiple	470 (72.5)	20 (3.1)	134 (20.7)	13 (2.0)	9 (1.4)	2 (0.3)	0 (0.0)	0 (0.00)	0 (0.0)	648
Other/Unknown	2777 (76.7)	46 (1.3)	715 (19.8)	38 (1.1)	29 (0.8)	5 (0.1)	6 (0.2)	0 (0.00)	5 (0.1)	3621

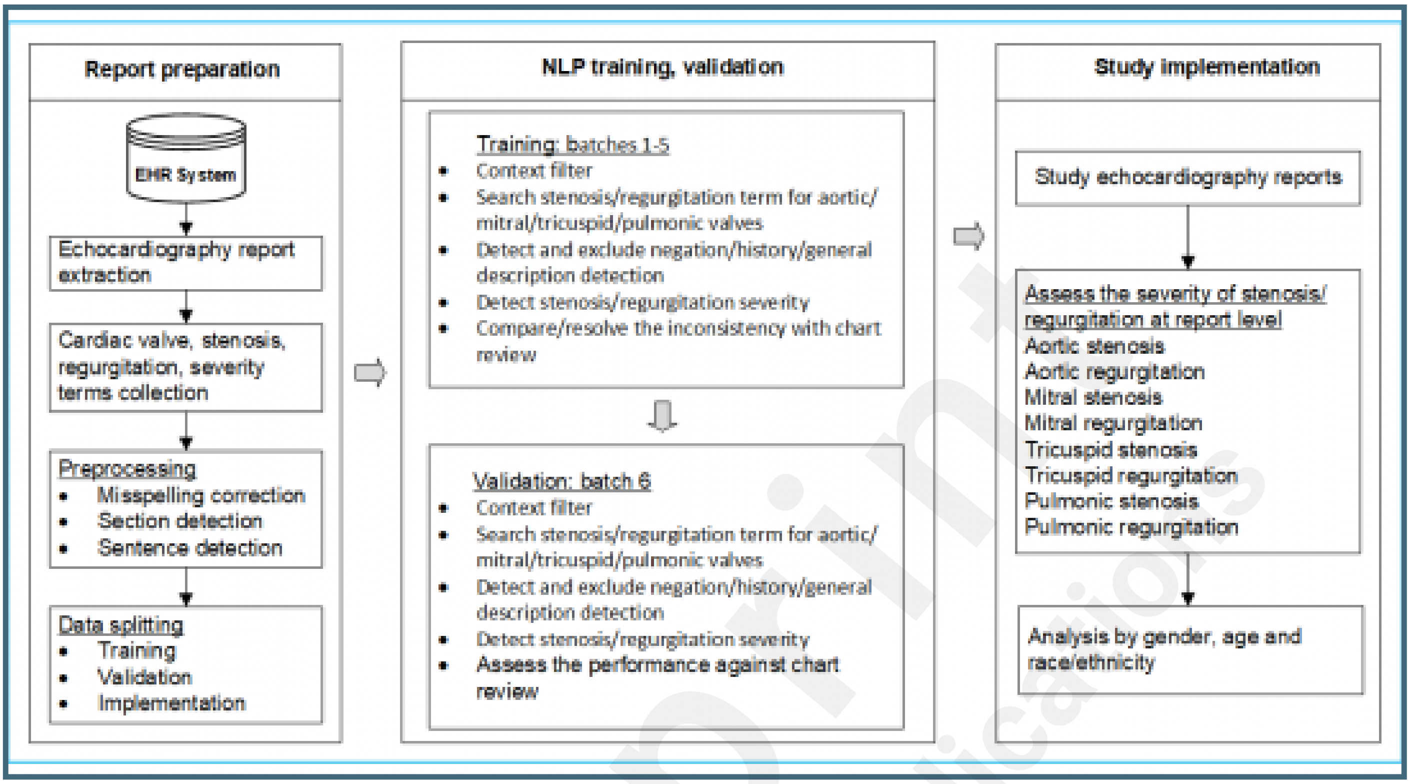
TTE: Transthoracic echocardiogram
KPSC: Kaiser Permanente Southern California

Figure 1. The schematic processing diagram describing the natural language processing algorithm for identifying the heart valve's stenosis and regurgitation from echocardiography reports.

Supplementary Files

Figures

The schematic processing diagram describing the natural language processing algorithm for identifying the heart valve's stenosis and regurgitation from echocardiography reports.



Multimedia Appendixes

The supplementary tables.
URL: http://asset.jmir.pub/assets/21de1d1ebe53c2c21047f89b60c89fd3.docx