A Method to Identify Potentially Preventable Readmissions from Historical Data

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Abstract
The topic of readmissions has become more prevalent in healthcare discussions in the past decade. Readmissions are linked to higher healthcare costs and could be used as a potential indicator of a breakdown in the quality of care at a facility. In an attempt to mitigate readmissions a recent strategy has focused on creating statistical models to predict a patient’s risk of becoming a readmission. However, one of the most important but arduous components of research on readmissions is to identify which patient visits in the data could be categorized as potentially preventable readmissions (PPR). This study develops a systematic method to define and identify PPRs from historical data. It relates primary and secondary diagnosis at both the admission and readmission events along with a set of criteria to filter the data. The PPR definition was validated against historical data obtained from CMS reports. The results show that the definition developed is consistent with CMS’ definition of a PPR. The benefit of using this methodology over CMS reports is attributable to the fact that CMS reports typically lag 6 months to 2 years from the time the readmission occurs whereas the proposed methodology can be implemented immediately after discharge.

Keywords
Readmissions, potentially preventable, ICD-9, planned vs. unplanned, related vs. unrelated

1. Introduction
Readmissions are increasingly more prevalent in healthcare discussions in the past decade as an indicator of a healthcare facility success. Readmissions, sometimes referred to as re-hospitalizations, are linked to higher healthcare costs and also as potential indicators of a breakdown in quality of care at a facility [1-3]. Therefore, readmission rates are progressively more accepted as a metric to ascertain a healthcare facility’s quality of patient care.

In March of 2010, the United States government signed into law comprehensive healthcare reform legislation, referred to as the Patient Protection and Affordable Care Act (PPACA), which was later amended by the Health Care and Education Reconciliation Act [4]. This legislation contains a number of provisions that change Medicare reimbursement in an effort to cut costs for the federal government. Among the provisions, there is one intended to reduce preventable hospital readmissions. The plan is to reduce Medicare payments to hospitals with relatively high preventable readmissions rates [4]. These preventable readmission rates are specifically related to the three core measures (diagnoses specific readmission rates) which the Centers for Medicare and Medicaid Services (CMS) tracks: Acute Myocardial Infarction (AMI), Pneumonia (PNM) and Congestive Heart Failure (CHF). The readmission rates for the core measures have been tracked by CMS for many healthcare facilities, and now through the PPACA would be used as a type of metric to determine a facilities quality of care. How CMS justifies which readmissions were preventable is loosely defined, but will essentially be reported by CMS as the readmission rate for that facility.
In an attempt to mitigate readmissions a recent strategy is creating models which can predict a patient’s risk of becoming a readmission [5-7]. These models can be powerful tools if implemented correctly and proven to be accurate for the intended population of the model. Therefore considerable value to patient quality of care could be created by functional readmission risk predictive models. These models would allow targeting the high readmission risk patients with precision, such that resources of a healthcare facility could be distributed to the patient population where the most benefit to cost is present. However, one of the most important but yet arduous components of research on readmission predictive models is to determine which patient visits in the data could be categorized as potentially preventable readmissions (PPR), which then becomes the response variable for the binary logistic regression models. A PPR may be defined as an unplanned, medically related readmission within a specified timeframe of a prior visit (typically 30 days) [8].

A majority of studies on predictive models for readmission target all types of readmissions or simply look at all unplanned readmissions [1, 4, 6-10]. However, Halfon et al. [8] argue that this approach is wrong as there might be a substantial number of readmissions that are unplanned but unrelated to the original admission. Some researchers argue that there is no uniform definition of “preventable” because quantifying “relatedness” is complex and seemingly unique to each patient [4].

Kansagara et al. [7] conducted a systematic review of risk prediction models for hospital readmissions. They found that out of 30 studies presented in their review, only one [8] attempted to define and identify PPRs (they called it potentially avoidable readmission). Halfon et al. [8], the authors of that study, developed a computerized algorithm to identify avoidable readmissions which includes a series of inclusion and exclusion criteria. In addition, the algorithm takes into consideration, among other variables, the Charlson comorbidity score [11] and the diagnosis related group (DRG). However, the algorithm still requires a thorough review (systematic review) of records by clinical experts. On top of that, the algorithm does not relate primary diagnosis to secondary diagnosis which might not be captured by the comorbidity score.

Similarly, Goldfield et al. [12] proposed another method to identify PPRs. However, comparable to Halfon et al. [8], their method required judgment of a clinical panel. The panel would determine if a readmission was related to an original admission for which the conditions seemed completely unrelated but had the possibility of being a complication from the original admission. This method hinders the possibility of automating the process of identifying PPRs as some cases would need to be evaluated on a case-by-case approach.

This research study presents a method to define and identify readmissions only using machine based classification of patient records. A set of rules were created which could allow researchers to automate the process of identifying readmissions from their historical data. It differs from Halfon et al. [8] and Goldfield et al. [12] in that it relates primary and secondary diagnosis at both the admission and readmission events along with the DRG. In addition, it uses a set of rules that do not require expert judgment or intervention; however, it should be noted that the rules were developed with the help of experts. With the proposed methodology researchers can first identify PPRs from their historical data in order to build predictive models which could then be used to identify and prevent future readmissions.

2. Case-by-case Approach

The definition of a PPR is necessary because readmission tracking is a more recent occurrence and unfortunately many healthcare providers do not include any indicators to know if a visit was a readmission. Though readmissions are indeed present, in many healthcare facilities they are never clearly recorded to indicate the visit as a readmission at a later stage.

From the researchers’ experience and a few cases reported in literature [8, 13-14, 18], some facilities undergo an inefficient and non-comprehensive case-by-case approach to identify readmissions similar to the following procedure:

- At the beginning of each month the lead case manager in the Case Management Department (or similar office) receives a list of patient visits from CMS of patients who the prior month were admitted to the healthcare facility within 30-days of a prior admission.
  - These visits are defined as a "readmission" because they are a visit within 30-days of a previous visit, but the true question of importance is whether or not these visits were related medically to a previous visit, making them "related readmissions".
- The list from CMS only incorporates patients who had government insurance of Medicare and Medicaid, while other insurance companies may question about a visit being a readmission upon request.
For this list the lead case manager then must review the visit, searching through available records, and justify in writing why or why not each visit is a related readmission.

Unfortunately this method leaves a lot of possibility for bias in the decision of a readmission being related, and has no real standard metrics to definitively indicate a readmission as medically related to a previous visit, but rather evaluates each individual case uniquely.

Furthermore, after the written justification for the readmission being related or not is submitted to CMS, sometimes it can be returned over-ruling the case managers decision and enforcing the visit as a readmission. This determination is by a separate case worker at CMS making a potentially biased decision, because no clear outline defining relatedness is established.

Once the decision of whether a readmission is related or not is established, it is marked down by CMS to be recorded for the readmission rate statistics. However, for most providers, the visit being branded a readmission is not recorded in their medical records system. This makes it extremely difficult when retrospectively looking back at patient data to know which patients are readmissions.

For this reason, it was necessary to develop some rubric to quantify a readmission and establish the type of readmission. In addition, research has found that the validity of the case-by-case review process is both inefficient and inconsistent [8, 13-14, 18]. CMS provides an algorithm that can be used to identify unplanned readmissions [19]. According to their report, they determine if a visit is planned or unplanned by simply looking at the primary discharge diagnosis of the readmission. As previously stated, this research proposes a new definition that relates primary and secondary diagnosis at both the admission and readmission events along with the DRG.

3. Identifying a Potentially Preventable Readmission

As previously stated, for the purpose of the research presented in this article, a PPR is defined as an unplanned, medically related readmission within a specified timeframe of a prior visit. In order to identify a PPR, it is essential to first determine the type of readmission; this includes timeframe, conditions, relatedness and if it is planned vs. unplanned.

3.1 Timeframe

For purposes of this research a 30-day timeframe was chosen. This is one of the most common timeframes reported in literature [7, 10]. More importantly it is the timeframe for which readmission rates are calculated by CMS and will be calculated for the PPACA legislation [4].

3.2 Readmission Categories

Typically there is no system in place to indicate if a patient visit was a planned/unplanned or a related/unrelated readmission. The definition of relatedness and planned/unplanned aspect of the readmissions was influenced by the document written by Stone and Hoffman [4] which summarizes “Rehospitalization: Understanding the Challenge”, a presentation given by Stephen F. Jencks, M.D., M.P.H, at the National Medicare Readmissions Summit in Washington, DC on June 1st, 2009. Jencks proposed at the Summit that any readmission within 30 days is a potential cost saving avenue and all readmissions within 30 days should be investigated [4]. While this is true, most of the potential for cost savings originates from the reduction in preventable readmissions [3, 8]. He also stated that further classifying readmissions into four proposed categories could help distinguish which readmissions were potentially preventable, and thus could be targeted for substantial improvement. The four categories are any variation of the following combinations: unplanned, planned, related, and unrelated. Table 1 shows the variations and a brief description of each combination for the classification of readmissions.

Upon further investigation a Planned-Related readmission is essentially unavoidable and just an extension of the previous care visit. An example of this is a follow-up inpatient surgery to a previous surgery, to complete more planned work. The two categories of unrelated readmissions are also not beneficial in reducing costs, because they are not related to the health issue being addressed at the first visit. For example, a planned knee surgery 20 days after a hospitalization for Pneumonia is planned-unrelated readmission because it is within 30 days. An unplanned-unrelated readmission example would be an admission for injuries sustained from a vehicle accident 10 days after being hospitalized for Pneumonia.
Table 1: Readmission Categories

<table>
<thead>
<tr>
<th></th>
<th>Planned</th>
<th>Unplanned</th>
</tr>
</thead>
<tbody>
<tr>
<td>Related</td>
<td>Planned and Related</td>
<td>Unplanned and Related*</td>
</tr>
<tr>
<td></td>
<td>Readmission is related to initial hospitalization diagnosis and scheduled or expected in advance.</td>
<td>Readmission is related to initial hospitalization diagnosis but is neither expected nor foreseen.</td>
</tr>
<tr>
<td>Unrelated</td>
<td>Planned and Unrelated</td>
<td>Unplanned and Unrelated</td>
</tr>
<tr>
<td></td>
<td>Readmission is not related to initial hospitalization diagnosis and is scheduled or expected in advance.</td>
<td>Readmission is not related to initial hospitalization diagnosis and is neither expected nor foreseen.</td>
</tr>
</tbody>
</table>

* PPR is defined as an unplanned and related readmission

The final category unplanned-related (shaded area in the table) is the target type of readmission where improvement could be made. This type of readmission indicates that a patient has returned to the hospital for the same or similar medical reason they previously were admitted for, and it was not planned but rather their health had deteriorated in some manner. This type of readmission has been termed a Potentially Preventable Readmission (PPR) because during the prior admit or shortly thereafter a gap in quality of care or condition occurred to allow the patient to relapse with the similar condition requiring hospitalization. PPR's have recently become more of a focus in healthcare, rather than all readmissions, because they hold the key to major cost reductions and improved quality of care.

3.3 Determining if a Readmission is Planned vs. Unplanned
Now that the scope of the readmission type has been determined the challenge is creating a method to be able to quantify patient visits as a readmission. This is currently one of the most difficult topics of readmission, because no proven global appropriate method to identify relatedness of visits has been formulated since medical interactions and scenarios are overwhelming complex [4].

To systematically decipher which patient visits were PPRs a method was devised to identify patient visits as planned vs. unplanned. This was followed by a set of rules which determine if separate visits were related. This method was developed after considerable discussion with healthcare professionals at the site where the research was conducted, as well as using a similar structure to the readmission identification methods found in the Horwitz et al. [1] and Krumholz et al. studies performed for CMS [15-17].

Therefore, using clinical expertise from doctors, nurses, and the case manager, along with literature definitions of unplanned visits, it was determined that for the facility where the research was conducted, an unplanned visit was one where the patient was admitted through the emergency department (ED). It should be noted this does not imply all ED admissions are readmissions, but rather that all unplanned readmissions are admitted through the ED. This is true for the reason that, at the facility where the research was conducted, if a patient needs to be admitted to the hospital without prior schedule (i.e. planned surgery stay) then even if it is not a life-threatening emergency, patients are admitted through the ED. Horwitz et al. [1] define an unplanned visit as those that required “urgent hospital management.” Thus a visit was unplanned if a patient is admitted through the ED and planned if admitted by some other method.

3.4 Determining if a Readmission is a Related Readmission
The method to define if two visits are “related” medically was constructed and vetted by expert nurses, coders, case managers and doctors with whom this research was discussed. Similarly to determining unplanned/planned, many discussions on the appropriateness of the developed relatedness method were conducted with healthcare professionals at the facility where this research was conducted.
Relatedness was determined using the ICD-9 codes in primary and secondary diagnoses, as well as Diagnosis-related Group (DRG) codes used to classify hospital cases (visits) commonly for insurance coding purposes. The proposed relatedness rubric to be constructed is unique to this research as no proven substitution for determining relatedness is currently available. The first and simplest rule to define relatedness was the case where a visit has the exact DRG as the readmission visit DRG. With identical DRG’s for these visits it is highly probable the patient was readmitted for similar or identical medical issues as before.

The next sets of rules involve relatedness based on the ICD-9 codes and are appreciably more complicated. Development of the proposed ICD-9 relatedness rules originated from the diagnosis-specific relatedness methods previously established in studies by [15-17]. In these studies the researchers created a detailed list of ICD-9 codes affiliated with the core measures, then if any of these codes was present as a diagnosis in the first visit, and any of the codes again found in the second visit, the visits were deemed related [15-17]. For example for the core measure of AMI all ICD-9 codes listed where in the 410.xx values, thus if any 410 code was present in both visits the readmission would be considered related. Stemming from these research reports it was determined appropriate to compare ICD-9 codes of similar diagnoses as being an indicator of medically related visits. In order to accomplish this, two styles of ICD-9 comparisons were used: an exact ICD-9 code match between visits, and a truncated ICD-9 code with just the primary digits being matched between visits. An illustration of these relatedness relationships is shown in Table 2.

For ICD-9 relatedness another level of complexity is present in reference to which diagnoses are to be compared. There are four possible comparisons between types of diagnoses: 1) readmission-primary diagnosis vs. prior admission-primary diagnosis, 2) readmission-primary diagnosis vs. prior admission-secondary diagnosis, 3) readmission-secondary diagnosis vs. prior admission-primary diagnosis, and 4) readmission-secondary diagnosis vs. prior admission-secondary diagnosis. These different comparisons were then evaluated for their relevance to potentially finding important information about the readmission. A key aspect to remember is that typically there is only one primary diagnosis but there could many secondary diagnoses listed in the patient record, at the research facility of this study up to 15 secondary diagnoses were recorded. Thus to compare one visit to another visit with secondary diagnoses, each of the secondary ICD-9 codes listed would have to be compared to a primary diagnoses, or to each of that visits secondary diagnoses.

The primary-primary comparison is important as a relatedness component because this means for both visits the patient had the same primary ICD-9 diagnosis. Similarly the readmission-primary to prior-secondary is deemed appropriate to evaluate because this could indicate a secondary diagnosis present previously that was inadequately treated and caused the patient readmission.

The opposite relationship, readmission-secondary to prior-primary, could also be indicative of related medical complications because the reason for the previous visit is still present at a large enough level to be a secondary diagnosis. These three comparisons were included for the relatedness rubric. The last comparison of secondary-secondary is not appropriate to include because a random secondary may be listed both times but truly not be influential into why the patient was re-hospitalized.

Upon review of this technique the nurses, coders, case managers and administrators believed this was an appropriate method to identify related readmissions from historical data. Future vetting of this methodology could be performed by a panel of experts including parties outside of the facility, to ensure this methodology for readmission identification is appropriate. Figure 1 depicts the ICD-9 relationship according to the definition developed in the methodology presented here.

<table>
<thead>
<tr>
<th>Table 2: Relatedness Method Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Relatedness Matching Criteria</strong></td>
</tr>
<tr>
<td>Exact Match</td>
</tr>
<tr>
<td>Truncated Match</td>
</tr>
<tr>
<td>No Match</td>
</tr>
</tbody>
</table>
The topic of relatedness increases in complexity due to the fact that some patients may have multiple visits within a 30-day timeframe and therefore each visit within the 30-day prior window must be tested against each other to determine if they are medically related. To help view how many previous visits of a patient were within 30 days prior to the visit being assessed, several simple temporary variables indicating the days since a prior visit were created. For the data used in this research, four temporary variables were created testing back to the 4th prior visit from each visit; at this point no patient had any 4th prior visits within 30 days. Therefore for this research it was only necessary to compare up to three previous visits if they were within the 30-day timeframe. This resulted in five different categories of relatedness, with comparisons occurring with up to 3 different visits, giving 15 possible combinations of relatedness. The visual illustration of these relatedness combinations is represented in Table 3.

All degrees of relatedness represented in the rubric were taken into consideration for readmissions, creating 15 temporary column variables for the identifier, and then combining all levels of relatedness into a single column variable coded as "Related". To establish which visits were related, complex search equations in excel were used to determine if a visit was related by any comparison, then these all had a separate indicator variable column to show "related" if appropriate. This might be useful in cases where researchers want to divide the data according to the type of relatedness.

The relatedness rubric development then accounts for relation by exact DRG code, exact ICD-9 code, and truncated ICD-9 code; while testing the current visit against all visits within 30-days and comparing primary diagnoses to primary diagnoses, as well as primary diagnoses to secondary diagnoses (as in Figure 1). Combining all of these the methodology to identify PPRs from historical data was then developed. It is depicted in figure 2.

### 3.5 Exclusion criteria

Prior to analyzing the data a set of criteria were used to exclude some patient records from the study. The exclusion criteria included: 1) admissions with discharge status of “left against medical advice” because the possible gap in quality of service was not under the control of the provider. This was consistent with what was reported by Goldfield et al. [12]; 2) Patients 17 years old or younger; 3) Patients transferred to an acute care facility (ACF), federal hospital, or psychiatric hospital as these facilities would be the entities responsible for the quality of care of the patient until discharge and thus, they are also responsible for any readmission.

### Table 3: Relatedness Rubric

<table>
<thead>
<tr>
<th>Relatedness:</th>
<th>Admit to Readmission Visit</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1st Prior Visit</td>
</tr>
<tr>
<td>Exact DRG - Exact DRG</td>
<td>Rel1-1</td>
</tr>
<tr>
<td>Exact Primary - Exact Primary</td>
<td>Rel2-1</td>
</tr>
<tr>
<td>Truncated Primary - Truncated Primary</td>
<td>Rel3-1</td>
</tr>
<tr>
<td>Truncated Primary - Truncated Secondary</td>
<td>Rel4-1</td>
</tr>
<tr>
<td>Truncated Secondary - Truncated Primary</td>
<td>Rel5-1</td>
</tr>
</tbody>
</table>
4. Identifying PPR and ATR Visits

Finally, with an "Unplanned visit" column and "Related" column created, the search for potentially preventable readmissions within 30-days could begin, since a PPR was established as an unplanned and related readmission [4]. The PPRs are suggested by Jencks et al. [3] as the type of readmissions that have the most potential for cost savings and therefore the primary focus of this research. Determining the PPRs was achieved by searching visit entries for being unplanned, related and within 30 days of a prior admission. The patient visits which met the unplanned, related and within 30-day criteria then could be flagged as a "Readmission" because these are the PPRs to investigate.

It should be noted that the purpose of identifying the PPRs was to then build predictive models that could aid in identifying patients with high risk of being a readmission. An important aspect when developing readmission predictive models is determining the appropriate patient visit information to evaluate. To predict a readmission before it occurs, information about the patient prior to the readmission must be used. Therefore, the most practical information to use is the information from the visit deemed the prior related admission to the readmission. This visit, referred to as "Admit to Readmit" (ATR), is the visit attributed as the theoretical cause for the re-hospitalization based on the PPR readmission criteria.

The ATR visit becomes a crucial component of the research because all the information about a patient, which can be used to develop predictive variables, should be found in this visit’s recorded information. Thus, after the PPR readmission visits have been determined, the ATR visits must be recorded as well and given an identifier in an “Admit to Readmit” binary column variable. The ATR visits then become the records to be analyzed for trends and patterns to attempt to create predictive models for readmissions.
Identifying the appropriate ATR visit was achieved by linking the prior visit number (1, 2 or 3) attached to the relatedness level corresponding to the visit through the temporary relatedness column variables. It was possible for a visit to have more than one level of relatedness, as well as being related to more than one prior visit. Redundancies in counting the number of PPRs was avoided by only indicating a visit as a readmission once. This was achieved through the use of "OR" statements in Excel, such that if any of the potential scenarios to mark a visit as a readmission were true the column variable would be marked "Readmission". Similarly to mark the ATR visits "OR" statements also were used, again only singly marking the ATR column variable for the respective visit's row with a "1" to indicate the patient visit was an admission to a visit marked as a PPR.

5. Method Validation

Patient records were obtained from a hospital located in the state of Montana for the time period of January 2008 through November 2013. However, in order to validate the proposed methodology the researchers needed a baseline for comparison or a “Gold Standard”. For this reason, CMS reports were obtained which revealed the ATRs for which CMS categorized a readmission as a PPR. Since typically hospitals do not get this report until 6 months to two years after the readmission event has occurred, the researchers were able to obtain only records for the time period of January 2008 through June 2011.

With the use of Excel, patient records were filtered using the rules previously defined and following the order presented in figure 2. After all the PPRs were identified, the original admissions to the readmission (ATR) were also identified. It should be noted that this process was done systematically using complex excel formulas. However, it was performed by one person without the intervention of any clinical expert. This was done to prove that this process could be automated at a later stage.

Finally, the research method was compared against the CMS report as presented in Table 4 which resulted in a sensitivity index (d’) of 1.628. It can be seen from the table that the proposed definition was able to identify 46 out of 55 ATRs resulting in a true positive rate of 83.64%. The methodology also resulted in a false positives rate of 25.85%. In a patient-centered healthcare system it is preferable to have higher false positives (25.85%) than misses (16.36%). This is due to the fact that it is better to give more care to a patient that is less likely to be re-hospitalized than not treating a patient with a high risk of readmission. Giving more care to a patient that has a low risk of becoming a readmission results in extra cost to the healthcare facility. However, not providing proper care to a high risk patient might result in adverse events to the patient which might even result in death.

Upon further investigation as to why the proposed methodology was not able to identify 9 of the readmissions, it was discovered that 4 of those 9 were actually planned readmissions. The researchers do not know why CMS considered those 4 as a PPR. Given the fact that CMS’s decision is the gold standard for this research, it is hard to make the case that CMS made a mistake (even though it is possible). Subsequently those 4 misses should then be attributable to some missing information that the researchers were not able to obtain from the records. The other 5 records were readmissions that, according to the definitions developed in this research, have no relationship with the original admission. It is on cases like these that make sense to have a panel of experts to treat them on a case-by-case approach. However, considering the fact that for this study those 5 records represent only 9.09% of the PPRs, this is not enough to justify the amount of work it requires to do a case-by-case analysis.

For research purposes, several definitions of PPRs were tested by relaxing the relatedness definition proposed in the methodology. This was done to explore the possibility of finding a better relatedness definition which could result in lower false positives.

<table>
<thead>
<tr>
<th>CMS (Gold Standard)</th>
<th>Research Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive (1)</td>
<td>46</td>
</tr>
<tr>
<td>Negative (0)</td>
<td>4970</td>
</tr>
<tr>
<td>Positive (1)</td>
<td>9</td>
</tr>
<tr>
<td>Negative (0)</td>
<td>14266</td>
</tr>
</tbody>
</table>

Table 4: Comparison of research method vs. CMS
The definitions that were tested included:

1. **Research def.** - the definition proposed by the methodology relating DRGs and ICD-9 both at the primary and secondary diagnoses.

2. **Research def. w/o DRG** - removing the DRG relatedness and only relating the ICD-9 codes.

3. **Relaxed research def.** - using DRGs and ICD-9 but removing the relatedness of readmission-secondary to prior-primary.

4. **Relaxed research def. w/o DRG** - removing the DRG relatedness from the previous definition.

5. **DRG only** - Using only the DRG.

Each definition was tested and plotted in a receiver operating characteristic (ROC) space as presented in figure 3. In an ROC space the best option is the one closest to the upper left corner, or the (0,1) coordinate, as this represents a case where all true positives (also known as hits) were identified with no false positives. From the figure it can be seen that the research definition provides the best ratio of True Positives/False Positives, closely followed by the research definition without the DRG relatedness. The other three definitions are successful at reducing the false positive rate at the cost of reducing the true positives as well. In fact, the third and fourth definition reduced the false positive rate by less than 10% at a cost of a reduction on the true positives of more than 30%. In this sense it is said that the other definitions are less sensitive. From the analysis it can be concluded that the definition developed for the methodology proposed in this article is the best one out of the possible definitions.

6. Conclusions

This research was motivated by the fact that the healthcare facility where the work occurred had no method of tracking their readmissions in a direct manner. There is no system in place to document if a visit was characterized as a readmission. This characterization occurs by the insuring parties of the patient such as CMS and other private sector insurers. Generally private sector insurers will characterize a visit as a readmission based on the CMS definition. However, this is not a simple, unbiased classification process due to the fact that case managers from CMS and the health facility both subjectively evaluate the patient record to determine if it was a readmission.

For this reason, a methodology was developed to identify PPRs and ATRs from historical data in those instances where the health providers do not keep record of their readmissions. The proposed methodology was tested using past CMS records as the gold standard. The results show that even though it is not a 100% accurate, the proposed methodology is able to identify more than 80% of the true positives at a cost of a 25.85% false alarm rate. With the definition in place on-going research is focusing on building predictive models for readmissions.
References


