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Using Rule-Based Logic to Streamline Patient Outcome Monitoring in a Multidisciplinary Diabetes Specialty Clinic

Joesph E. Capito

Department of Family Medicine, West Virginia University, Morgantown, WV, USA
Email: jcapito2@hsc.wvu.edu

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Abstract

Background: Data collection for research and quality improvement can be resource-intensive, often requiring manual chart reviews. This challenge was evident in a multidisciplinary diabetes clinic within an academic family medicine practice. Traditional methods for evaluating metrics relied on time-intensive processes, hindering efficient quality assessments. Objectives: To develop a streamlined, rules-based reporting solution within Epic EMR to simplify data collection and demonstrate patient outcome improvements, specifically hemoglobin A1c levels, in a multidisciplinary diabetes clinic. Methods: A series of custom rules were created to identify clinic visits, capture baseline and follow-up metrics, and generate automated reports for analysis. The rules included specifications for identifying clinic visit types, calculating first and last visit dates, and retrieving laboratory data for pre- and post-clinic comparisons. These rules were then used to populate columns in a reporting workbench for real-time data display. Results: The rules-based reporting solution yielded a dataset of 151 patients, with metrics including pre- and post-clinic hemoglobin A1c values, visit counts, and outcome trends. Conclusions: Informatics-driven solutions like this rules-based reporting system can significantly reduce the burden of data collection for research and quality improvement initiatives. This approach enhances the capacity for real-time outcome monitoring and supports the integration of evidence-based practices in clinical settings.

Keywords

Electronic Health Records and Systems, Quality, Diabetes, Biosurveillance, Case Reporting

1. Introduction

Conducting research and quality improvement in clinical settings can be challenging due to the time-intensive nature of data collection. This is particularly true in multidisciplinary clinics, where manual chart reviews and data extraction from various sources can be overwhelming. In one academic family medicine clinic hosting a multidisciplinary diabetes clinic, evaluating patient outcomes such as hemoglobin A1c (HbA1c) levels was a complex and resource-intensive process. Traditional methods of data collection hindered efficient monitoring and analysis of clinical outcomes, making it difficult to assess the effectiveness of interventions [1].

For clinicians primarily engaged in patient care, maintaining a comprehensive list of all patients seen in a given clinic—along with their initial appointment date and relevant pre- and post-intervention metrics—can be a significant burden. Even when such lists are created, manually extracting data from individual patient charts and tracking changes over time remains labor-intensive and inefficient. Prior studies have demonstrated that manual chart reviews are both time-consuming and prone to errors, highlighting the advantages of computer-assisted data extraction in improving efficiency and accuracy [2].

This paper presents a solution to this challenge: the development of a rules-based reporting system within Epic EMR. By automating the data collection and reporting processes, this system simplifies the extraction of relevant metrics and allows for real-time analysis of patient outcomes. The aim is to showcase how informatics tools can be used to streamline data reporting, ensuring that valuable insights are readily available to clinicians and researchers while reducing manual workload. Specifically, this project demonstrates the creation of a report tracking changes in HbA1c levels among diabetes clinic patients, illustrating how such a solution can be replicated across other clinical contexts.

2. Objectives

To outline the methodology for designing and implementing a rules-based reporting solution in Epic EMR for a multidisciplinary diabetes clinic. This paper provides a step-by-step guide to system configuration, data extraction, and visualization, offering insights for informaticists and healthcare teams seeking to enhance real-time clinical data accessibility and workflow efficiency.

3. Methods

To automate the data collection process, a series of rules and reporting configurations were built in Epic EMR. These rules ensured accurate identification of patient data from the multidisciplinary diabetes clinic, including first and last visit dates, lab values, and visit counts. Below is a step-by-step outline of the methods used:

Rule 1: Identifying Relevant Clinic Visits

A **Patient** rule was created to capture all relevant clinic visits (DM Clinic Visit

Type). The rule criteria were:

- **Property**: Appointment Visit Type; **Operator**: Contains Any; **Value**: "New Diabetic Visit," "Return Diabetic Visit."
- **Property**: Encounter Department; **Operator**: Equals; **Value**: "Family Med-***."

An **AND** logic was applied to ensure both conditions were satisfied, thus isolating visits in the desired department with specified visit types.

Rule 2: Determining the Date of First Visit

A **Registry Metric** rule (DM Clinic First Visit) was created to determine the date of each patient's initial visit to the diabetes clinic. The criteria included:

- Property: First Encounter Date; Operator: Does Not Equal; Value: Null; Result: Property Column Value

This property was customized as follows:

- Encounter types excluded: Orders Only
- Appointment statuses excluded: No Show, Canceled, Left Without Being Seen
- Rule Filter: DM Clinic Visit Type (Rule 1)
- Lookback Period: 3650 [days]
- Start date: T[oday]

Using Property Column Value as the result ensured that the date of the patient's first visit to the diabetes clinic would be displayed.

Rule 3: Defining the Pre-Clinic Data Period

A **Registry Metrics Search Period Filter** rule (DM Clinic Pre-Clinic Data) was built to identify the timeframe for retrieving pre-clinic data. The criteria included:

- Property: Search Period By Rule; Operator: Does Not Equal; Value: Null

This property was customized as follows:

- Latest Date Rule: DM Clinic First Visit (Rule 2)
- Latest Data Source: Internal Only
- Relative latest date: y/m/d
- Earliest Date Rule: DM Clinic First Visit (rule 2)
- Earliest Data Source: Internal only
- Relative earliest date: Y[ear]-1/M[onth]/D[ay]

This setup ensured that the pre-clinic data corresponded to the year leading up to each patient's initial visit.

Rule 4: Retrieving Pre-Clinic Hemoglobin A1c (HA1c)

A **Patient** rule (DM Clinic Pre-Clinic HA1C) was created to retrieve the last HA1c value recorded during the pre-clinic period. The criteria included:

- Property: Last Lab Value; Operator: Does Not Equal; Value: Null

The property was customized as follows:

- Common Name: HA1c.
- Search Period Filter Rule: DM Clinic Pre-Clinic Data (Rule 3)

The return message displayed the last lab value meeting the criteria, showing the most recent HA1c obtained before the first clinic visit.

Rule 5: Determining the Date of the Most Recent Visit

A **Registry Metrics Rule** (DM Clinic Last Visit) was created to determine the date of the patient's most recent visit. The criteria included:

- Property: Last Encounter Date; Operator: Does Not Equal; Value: Null; Result: Property Column Value

The property was customized as follows:

- Encounter types excluded: Orders Only
- Appointment statuses excluded: No Show, Canceled, Left Without Being Seen
- Rule Filter: DM Clinic Visit Type (Rule 1)
- Lookback Period: 3650 [days]
- Start date: T[oday]

The result of this rule was set up to display the property column value so the date of the patient's most recent visit to the specialty clinic could be obtained.

Rule 6: Defining the Post-Clinic Data Period

A **Registry Metrics Search Period Filter** rule (DM Clinic Post-Clinic Data) defined the timeframe for capturing post-clinic data. The criteria included:

- Property: Search Period By Rule; Operator: Does Not Equal; Value: Null

The property was customized as follows:

- Latest Date Rule: DM Clinic Last Visit (Rule 5)
- Latest Data Source: Internal Only
- Relative latest date: Y[ear-1]/M[onth]-6/D[ay]
- Earliest Date Rule: DM Clinic Last Visit (rule 5)
- Earliest Data Source: Internal only
- Relative earliest date: y/m/d

This ensured that post-clinic data reflected a relevant follow-up period for each patient.

Rule 7: Retrieving Post-Clinic Hemoglobin A1c (HA1c)

A **Patient** rule (DM Clinic Post-Clinic HA1C) retrieved the most recent HA1c value recorded during the post-clinic period. The criteria included:

- Property: Last Lab Value; Operator: Does Not Equal; Value: Null

The property was customized as follows:

- Common Name: HA1c
- Search Period Filter Rule: DM Clinic Post-Clinic Data (Rule 6)

The return message displayed the last lab value meeting the criteria, showing the most recent HA1c obtained before the first clinic visit.

Rule 8: Counting Total Clinic Visits

A **Patient** rule (DM Clinic Visit Count) calculated the total number of visits a patient had within the clinic. The criteria included:

- Property: Number of Visits with LOS (Level of Service) Filed in Date Range; Operator: Does Not Equal; Value: Null

The property was customized as follows:

- Start Date: 120 months ago
- End Date: T (current date)
- Encounter Filter Rule: DM Clinic Visit Type (Rule 1)
- E&M Procedure Grouper: DM Clinic Custom Billing Grouper (explained later)

The return message was the same LOS Filed in Date Range, thus displaying the total number of visits a patient had in the multidisciplinary clinic.

To make the custom grouper, an analysis in Epic's SlicerDicer was done. Using the Base of All Patients, and the criteria of Visit Type: New Diabetic, Return Diabetic Visit linked with the criteria Encounter Department: Family Med ***, the patient panel was sliced by LOS, grabbed by top 5 over the past 10 years. Only 4 different LOS were used. These 4 LOS were used to make a Procedure Masterfile (EAP) grouper of the type General. The 4 sliced records were then entered into the general info field of the grouper.

Rules 2, 4, 7, and 8 were then turned into respective Extensions (LPP) (Type: AS Reports PAF Extension; Code template: ADT Rule Evaluation; Database" Patient, Registry Data, Patient Lists). The extensions were used to create respective Columns (PAF) using the Field type: Extension and Master file: EPT—Generic Patient Data." These columns were then added to a report that used the criteria All Patients AND Alive AND Encounter department Family Med-*** and Appointment Visit Type New Diabetic OR Return Diabetic Visit with a lookback time of 5 years.

4. Results

This report yielded 151 patient results, with data on total visits, first visit date, pre-clinic HbA1c, and post-clinic HbA1c (**Figure 1**). The mean pre-clinic HbA1c was 9.87%, and the mean post-clinic HbA1c was 7.91%, reflecting a substantial reduction. A paired t-test ($t (150) = 9.65$, $p < 0.0001$) revealed a statistically significant improvement in A1c levels, supporting the effectiveness of the multidisciplinary approach. The average reduction in A1c was approximately 1.96%, demonstrating the clinic's positive impact on patient outcomes.

Total Visit Count	First Visit Date	Pre BMI	Post BMI	Pre Chol	Post Chol	Pre HDL	Post HDL	Pre HA1c	Post HA1c
8	7/23/2024	25.53	24.58	133	129	71	69	9.1	7.7
7	5/14/2024	29.85	25.36	241	127	47	37	11.1	6.6
7	3/12/2024	29.47	29.78	211	177	32	31	9.1	9.4
5	10/17/2023	31.9	32.7	179	141	43	45	9.2	6.8

Figure 1. A sample from the diabetes clinic report showing how data from the clinic appeared to the end user.

5. Discussion

This project highlights the potential of clinical informatics to reduce the manual workload associated with data collection and enhance the accessibility of real-time clinical data. By leveraging Epic EMR's custom rules and reporting configurations, we were able to automate the extraction of key metrics from patient visits, including HbA1c levels before and after clinic participation. This streamlined approach not only saved time but also ensured the accuracy and consistency of the data being reported.

Without a structured framework like the one outlined in the methods section, this project required approximately 12 hours of dedicated analytics time, and the data can be re-generated at any time, without any repeat buy-in labor for chart review. West *et al.* previously analyzed the financial burden of data collection and reporting for diabetes quality improvement initiatives in primary care settings, estimating an implementation cost of approximately $15,552 per practice, with annual maintenance expenses of around $9,553 per practice [3]. Using the figure from that study, larger healthcare facilities may incur information support costs approaching $10.00 USD per patient per year. By streamlining data extraction and analysis, the approach presented in this project has the potential to markedly reduce both labor and financial burdens associated with ongoing quality improvement and research efforts.

One of the key strengths of this solution lies in its scalability and adaptability. The rules-based reporting system can be tailored to various clinical environments, enabling a wide range of metrics to be tracked efficiently. While this project focused on monitoring HbA1c levels in a multidisciplinary diabetes clinic, similar rule-based methods can be applied across different specialties. For example, in cardiology, the system could track blood pressure trends and medication adherence among hypertensive patients. In pulmonology, it could monitor lung function metrics such as FEV1/FVC ratios in COPD patients. For preventive medicine, the rules could be designed to identify patients overdue for cancer screenings, vaccinations, or annual wellness visits. If a provider or institution has specific clinical priorities, the framework can be adjusted by modifying inclusion criteria, timeframes for data extraction, and outcome measures to fit their needs.

However, the development and implementation of this reporting solution were not without challenges. The complexity of mapping structured data fields within Epic EMR required significant planning and expertise, especially to ensure that data from various sources were accurately captured and integrated. Additionally, maintaining the accuracy of the report required ongoing validation, making it essential to regularly review the system for discrepancies or errors. Despite these challenges, the solution proved to be an effective and repeatable method for data extraction and reporting.

6. Conclusions

This project demonstrates the value of applying clinical informatics to improve the efficiency and accuracy of data collection in multidisciplinary clinics. By creating a rules-based reporting system within Epic EMR, we were able to streamline the process of tracking patient outcomes, providing clinicians with real-time, actionable insights into the effectiveness of care. The success of this approach underscores the potential for informatics-driven solutions to enhance clinical decision-making, reduce manual labor, and support quality improvement initiatives across various healthcare settings.

The method described in this paper offers a repeatable framework for others seeking to implement similar systems within their own organizations. The adaptability of this reporting solution means it can be applied to a wide range of clinical contexts, enabling healthcare teams to monitor patient outcomes more effectively. Ultimately, this approach improves patient care, supports evidence-based practices, and facilitates the integration of continuous improvement into daily clinical workflows.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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