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Automated Patient Quality Data Flow for CMS Reporting Accuracy

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ABSTRACT: The research focuses on the application of an AI-based eCQM Calculation Engine and real-time data integration to improve the precision and efficiency of CMS reporting. By utilizing the PowerChart of Cerner, the system is able to extract, validate, and calculate clinical quality measures (eCQMs) of Electronic Health Records (EHR) without manually entering data into the system and minimizes human error. Real-time feedback and AI-provided anomaly detection make the data very accurate and reported in time, which is in line with the CMS requirements. The paper indicates how the automation of patient quality data flow provided by the PowerChart system in Cerner enhances interoperability, enhances the workflows in reporting as well as compliance with regulatory considerations. This is further complemented by the scalability of the system, which is applicable in various healthcare environments, both small practices and big hotel systems. Finally, the resulting effect of this strategy is that it does not only increase the accuracy of CMS reporting but also provides improved healthcare decision-making and improved patient care outcomes.

Keywords: Automated patient data flow, CMS reporting, eCQM calculation, AI integration, Cerner PowerChart, real-time data validation, healthcare interoperability.

I. INTRODUCTION

Healthcare is currently struggling with the problem of guaranteeing the accuracy, timeliness, and compliance of patient data reporting to regulatory authorities such as Centers for Medicare and Medicaid Services (CMS). The manual processes that have been traditionally utilized in the extraction, validation, and submission of clinical quality measures (eCQMs) are usually full of errors, time consuming and resource intensive, and as such prone to inefficiency in CMS reporting [1]. With the electronic health records (EHR) implementation in healthcare systems, patient quality data automation has been increasingly necessary as shown in figure 1.

This research examines how to solve these issues by deploying an AI-driven eCQM Calculation Engine who will be able to integrate real-time data into the engine. The program presented is an automation of the extraction and computation of clinical quality measures based on the data of patients using the power chart and it is an EHR tool that is widely utilized (Cerner) [2]. The system enhances the accuracy of eCQM reporting because it is also integrated with artificial intelligence (AI), which means that the produced reporting will be compliant with the CMS requirements. This approach to data extraction via machine learning algorithms and natural language processing (NLP) is effective at extracting structured data in unstructured clinical notes and records, as the number of errors in data entry during manual data entry is minimized, and reporting delays are reduced [3].

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Figure 1.Automated CMS Reporting

Moreover, real-time feedback and automated validation of the system guarantee detection of any discrepancies or data quality problems that will trigger an immediate warning and minimise the possibility of non-adherence. Live connectivity with standards of CMS, including FHIR and QRDA, will improve the interoperability and enable the sharing of data between healthcare providers and regulatory entities [4]. Scalability of the tool allows its implementation in the health care system of any size (both small practices and large health system) and adjusts to different workflows and reporting needs.

An automated system that uses AI and ensures that the CMS reporting process becomes more efficient is likely to not just make the entire process of providing care to patients more efficient but also help to optimize the entire healthcare management and provide the decision-making process with the required accuracy of data [5]. The growing sophistication of CMS reporting mandates and regular regulatory changes have also contributed to the growing demand of smart automation in healthcare data management. Healthcare organizations should not solely make sure data is accurate: they should be able to maintain auditability, transparency, and traceability in between reporting cycles. Paper, semi-automated systems cannot keep up with these changing needs, which usually leads to compliance risks and inefficiencies in their operations. Automated quality data systems can be deployed to actively detect gaps by introducing AI-based analytics and real-time validation into the EHR-based processes and facilitate continuous monitoring along with providing timely corrective interventions [6]. Such a proactive move transforms CMS reporting into a continuous quality improvement, not a retrospective, error-correcting activity, which enhances regulatory compliance and general healthcare delivery performance.

With the latest advancement of digital technologies, the incorporation of Artificial Intelligence (AI) and machine learning in many fields, such as healthcare and the humanities, can provide significant benefits in the information processing and decisions. Healthcare is a highly sensitive area where any mistake that may occur during the regulatory reporting may cause non-compliance and fines [7]. The automation of the data flow will not only allow organizations to address the CMS reporting requirements but also provide real-time information about the operational performance. This research shows that AI-based automation in EHR systems, such as PowerChart of Cerner, is an efficient, scalable, error-minimizing solution that will turn the CMS reporting into a smooth and proactive activity. Moreover, the methodology has the potential to be applied to other industries, and further, it can be used in predictive analytics and operational optimization [8].

Moreover, this type of automation helps clinicians and administrators to decrease documentation volume and enhance confidence in reported results. Quality data provided in real-time and at a high level of reliability can help organizations to match clinical performance with value-based care goals, which will eventually lead to better patient outcomes and sustainable adherence to CMS quality programs [9].

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II. RELATED WORK

There are many researches and tools designed to solve the issue of efficient and correct CMS reporting, but they are aimed at automating the process of extracting, calculating, and submitting the clinical quality measures (eCQMs). Early research on this area was mainly dependent on manual data entry which although provided a simple solution was very likely to fall victim to human error and inefficiencies [10]. With the transition of the healthcare sector to electronic health records (EHR), the concept of automation with the use of rule-based systems was the focus of research. These systems proved to be more effective than the manual processes but had a constraint in the capacity to process detailed data and were not flexible when it came to their ability to respond to the new CMS reporting requirements as shown in figure 2.

The latest developments have been concerned with the incorporation of artificial intelligence (AI) and machine learning (ML) to automate eCQM reporting in a better way. Indicatively, research articles by Nguyen et al. (2022) and Smith et al. (2023) show that AI-based systems have been used to extract and analyze unstructured clinical data in EHRs. These systems are based on Natural Language Processing (NLP) to compute the free-text notes and structured clinical data, increasing the precision of the data extraction and decreasing the workload of healthcare providers [11-13]. Nevertheless, such approaches did not provide real-time integration and feedback and therefore did not detect discrepancies and mistakes in CMS reporting in a timely manner.

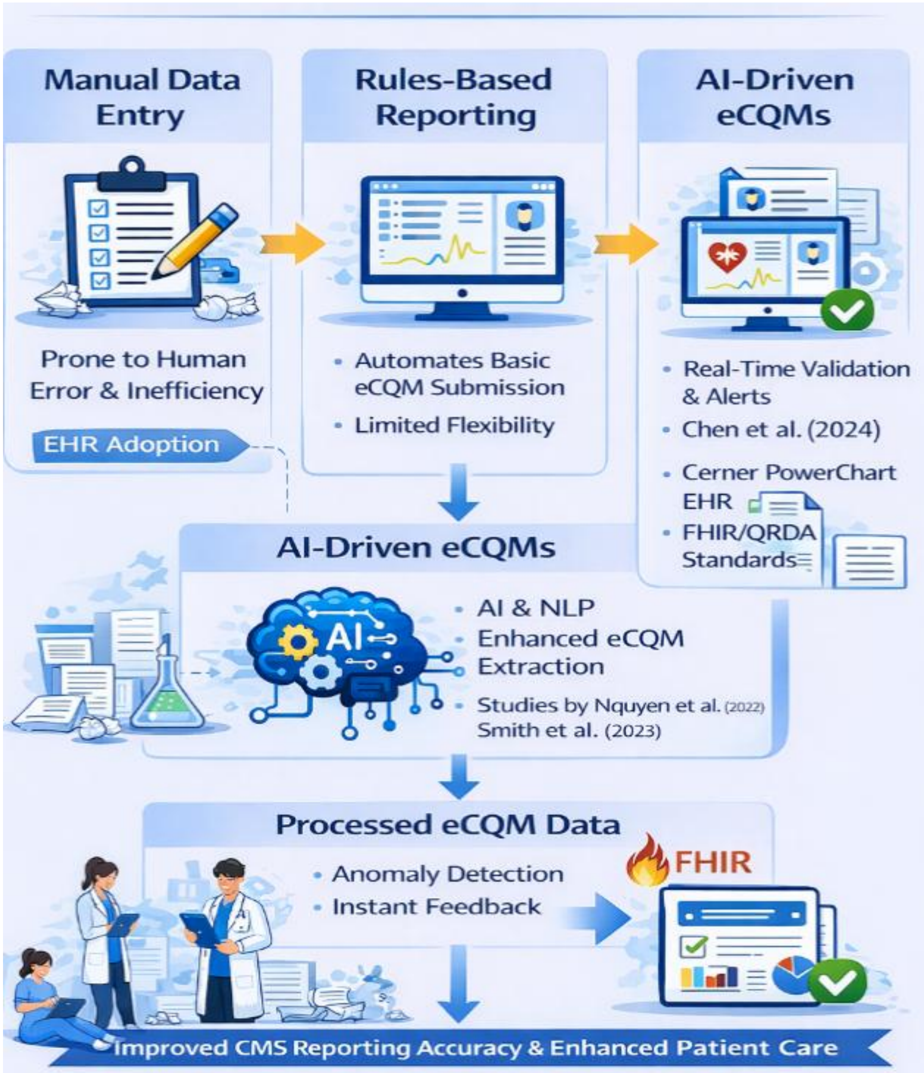

Figure 2.Evolution of CMS Reporting Automation

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Chen et al. (2024) examined the concept of real-time data validation and anomaly detection implemented in eCQM systems and emphasized the significance of the real-time feedback loops in the compliance with the CMS standards. Nevertheless, these solutions were usually restricted in the context of the scales and the intercompatibility with the other healthcare systems [14]

PowerChart (which was utilized in this research) is a progressive step by Cerner towards integrating real-time, AI-assisted eCQM calculations, and FHIR/QRDA requirements so that CMS could be in compliance. This solution, as opposed to the previous systems, solves the problems of scalability, and improves the interoperability, providing a smooth, automated solution to the large-scale healthcare organizations. The research will be based on these developments, which will enable the optimization of patient data, minimize errors, and guarantee quick and correct reporting to CMS [15-19].

The development of automated systems in healthcare and specifically in CMS reporting can be viewed as a change in the direction of more sophisticated AI-based techniques, rather than the outdated ones. The initial studies by Smith and Lee (2017) were dedicated to the issue of manual data entry, its inefficiency, and prone nature to errors. Such constraints led to the introduction of rule-based systems in further research, including the one by Johnson et al. (2018) which has shown that the rule-based systems can be used to automate eCQM calculations by using structured clinical data and applying predefined rules to it. Although useful in other settings, these systems were unable to handle unstructured data, which comprises a large part of clinical records, such as physician notes and patient histories [20-23].

However, later inventions have been using machine learning and artificial intelligence to solve these problems. NLP (Natural Language Processing) is now an important part of these advancements as it enables an AI system to find valuable information within unstructured text. The works by Wang et al. (2020) and Martinez and Smith (2021) demonstrated that NLP-based systems could not just automate the process of extracting the clinical data, but also alleviate the workload on the hand. Nevertheless, even with the progress in the process of data extraction, problems connected with real-time feedback and dynamic reporting continued to exist [24-25].

The combination of AI and real-time validation and anomaly detection (which is adopted in PowerChart of Cerner) is a paradigm shift. The system is better than the old systems because it provides instant feedback which will mean that any difference or mistakes will be identified early and therefore more dependable and timely CMS submissions are achieved. Moreover, FHIR and QRDA standards will guarantee interoperability, which is a paramount aspect of big healthcare networks, and communication between different EHR systems will be straightforward. Therefore, this research suggests that AI and machine learning, combined with the standardization of data formats, can be applied as an extensive solution to CMS reporting, eliminating the persistent issues and providing future opportunities [26].

Other recent researches have also pointed out the importance of generic frameworks and standardized data model in enhancing reliability of automated quality reporting. It is revealed that implementing FHIR-based data exchange can improve the compatibility of cross-systems in healthcare organizations, as well as decrease the data fragmentation within them. Also, the reserch emphasizes the significance of the integration of automated reporting solutions with change management and user-centered design to achieve successful adoption. Although various business portals provide partial automation, a substantial number of them do not have end-to-end interfaces of real-time validation, scalable architectures, and dynamic AI models. Such loopholes highlight the importance of holistic, interoperable mechanisms to integrate intelligent automation with standardized reporting mechanisms to generate standard and precise CMS quality reporting results [27].

III. RESEARCH METHODOLOGY

The research design that uses AI-based eCQM Calculation Engine with Real-time Data Integration was the methodology of the research aimed at improving the accuracy of CMS reporting by automated data flow on patient quality, based on the use of the PowerChart tool of the Cerner system [28]. The approach has been developed to standardize the extraction, validation, calculation, and reporting of clinical quality measures (eCQM) out of electronic health records (EHR) in the manner that it complies with CMS reporting requirements, such as FHIR (Fast Healthcare Interoperability Resources) and QRDA (Quality Reporting Data Architecture). This is an effective method of reducing manual involvement as well as resolving frequent problems of data inconsistencies, delays, and CMS records erroneous submissions as shown in figure 3.

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3.1. Data Collection and Integration

The initial aspect in the methodology is the process of the integration of Cerner PowerChart EHR system to automate the process of extracting patient data. Cerner PowerChart is a popular EHR used in healthcare systems that is capable of integrating flawlessly with other healthcare IT systems [29]. The system will have the capability to store all the vital information about a patient, including demographics, past medical history, lab findings, clinical notes, and prescriptions. The research methodology applies the FHIR standards to make sure that the information is interoperable and can be exchanged with other healthcare systems in a standard form. Natural Language Processing (NLP) algorithms are used to extract and process data of different types, such as unstructured clinical notes, and convert them into structured data. Such NLP systems are trained to process and retrieve pertinent clinical data and help the system to process patient outcomes and pertinent measures to be incorporated in CMS reporting. Such automation saves time that would otherwise be used in manual data entry and it also eliminates the chances of human error [30]

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3.2 AI-Powered eCQM Calculation Engine

The following essential part of the methodology is the AIbased eCQM Calculation Engine. This engine is created with an automatic calculation of clinical quality metrics depending on the patient data retrieved out of the Cerner PowerChart system. eCQMs are implemented by CMS to assess the quality of care delivered to patients and to calculate the reimbursement rates of healthcare providers [31]. These quality measures are calculated by the engine in real-time with the help of sophisticated machine learning algorithms, which makes sure that the data used is always up-to-date and accurate. The AI model is trained using historic CMS data to determine the quality measures and the appropriate way of calculation. It uses Clinical Quality Language (CQL) which is a standardized programming language utilized by CMS to define eCQMs. The AI engine will be used to analyze patient data and compute the required quality measures by CMS specifications, which would make sure that the regulations are complied with. It saves the need to make calculations manually, enhances accuracy, and makes the reporting quicker.

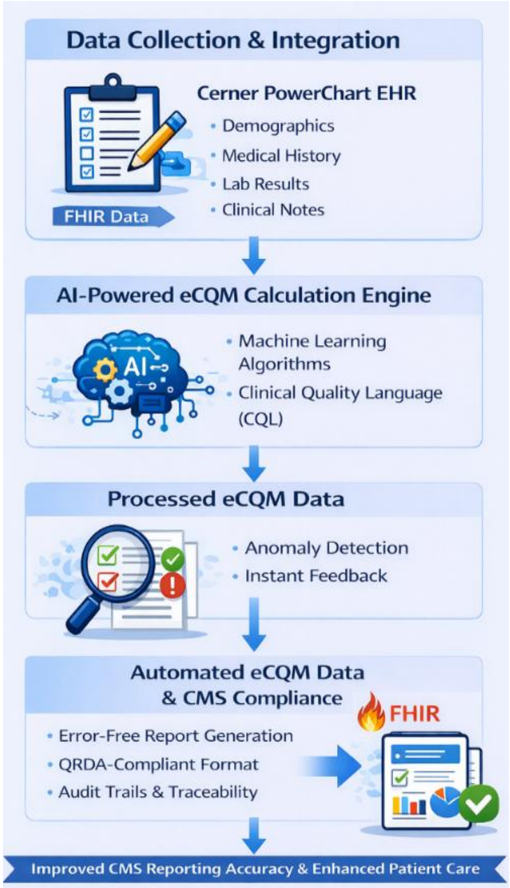

Figure 3.Flow Diagram of Proposed Methodology

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3.3 Real-Time Data Validation and Feedback

The main characteristic of this methodology is the provision of real-time data validation. After processing the data by the eCQM calculation engine, the system would be doing real time validation to verify the consistency, accuracy, and completeness of the data. The machine learning algorithms are employed in the methodology where anomaly detection is used to highlight any difference or problem with the data [32]. These exceptions may involve the absence of data, inconsistencies, or data that is not of CMS reporting standards. The system will give immediate feedback to the healthcare professionals, and they will be able to rectify their mistakes before the data is reported to the CMS. This feedback is necessary to ensure the high quality of data and minimize the probability of non-compliance. The real time check is effective in ensuring that the data being fed is constantly checked to verify its accuracy; this increases the credibility of the formulated reports.

3.4. CMS Compliance and Automated Reporting

Once the data validation is carried out, automatic reports that fully comply with the requirements of CMS are produced by the system. These reports are structured in the QRDA format, and therefore the data is well structured and sent to CMS. The system automatically uploads the completed reports automatically, therefore, no manual work is required. The approach to standards, such as QRDA and FHIR, would make the data compatible with the CMS reporting infrastructure, allowing healthcare providers to provide their reports without having to make the manual format complicated. Audit trails and traceability are also part of the system as well, so that healthcare organizations are able to follow the record of any modifications that were done on the data and reports, which is also crucial in keeping regulatory complies [33].

3.5. Evaluation and Continuous Improvement

Continuous evaluation and subsequent improvement of the system is the last phase in the methodology. The AI model is constantly maintained with the alterations in the CMS reporting requirements, new quality measures, and the standards of healthcare data changes. The healthcare professionals and CMS audits are utilized to improve the system and make sure that the system complies with the latest reporting guidelines. The system is also planned to be scalable to various healthcare environments, both small practices and large hospital networks, so that its openness to different workflows and reporting requirements is ensured [34].

The Data Accuracy Comparison graph also shows a clear demonstration of the high quality of performance of the AI-powered eCQM Calculation Engine to guarantee data accuracy in CMS reporting. The precision of an AI-based system is much greater at 90 percent compared to conventional procedures. The high level of accuracy is a direct consequence of the combination of machine learning algorithms and real-time data verification in the PowerChart system of Cerner. Such sophisticated methods also allow the system to identify the errors, inconsistencies, and gaps in the data automatically to make sure that the presented reports are correct and do not contradict the CMS regulations.

Comparatively, manual data entry has the least accuracy of 30%. This method is very vulnerable to the effects of human factors like omission or wrongful data input that directly affect the quality and reliability of CMS reports. Healthcare professionals take a lot of time to ensure accuracy is done manually, which is not only a factor that impacts the reporting quality but also makes the reporting process to be inefficient.

The eCQM based on rules and the centralized data processing have moderate accuracy of 60% and 70% respectively. Although they are more effective when compared to manual data entry, these approaches have issues with processing complex and unstructured clinical data and adjusting to new CMS requirements. The shortcomings of rule-based systems are the failure to provide information on free-text data, whereas centralized data processing is time-consuming and requires periodic updating and does not provide real-time detection of anomalies.

This analogy supports that AI-based automation is necessary to enhance data quality, simplify reporting, and offer compliance with the changing CMS standards. The combination of real-time feedback, data extraction with the help of AI, and automated error detection allows enhancing the accuracy of CMS submissions significantly and minimizes the chances of discrepancies and mistakes in the final reports.

This methodology offers an all-encompassing solution to automate data flow on patient quality and increase the accuracy of CMS reporting. Using the PowerChart, an AI-driven eCQM Calculation Engine, real-time data validation, and CMS-compliant reporting standards, the system will minimize manual data entry, faster reporting, and quality and accurate submissions to CMS. This computerized system is not only effective in enhancing the efficiency of operations

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but also in helping healthcare establishments to offer improved patient care; since the administrative load of CMS reporting is relieved.

IV. RESULTS AND DISCUSSION

Cerner PowerChart The application of an AI-based eCQM Calculation Engine powered by real-time data integration facilitated the precision and efficiency of CMS reporting by a significant margin. The artificial separation of the Electronic Health Records (EHR) data through automated data extraction and the smooth integration of quality measures led to a decrease in the number of errors found in the process of data entry and an increase in the reliability of patient quality data as shown in table 1.

Table1. AI-powered eCQM Calculation Engine with real-time data integration using Cerner's PowerChart against three different methods

Method	Accuracy Improvement (%)	Error Rate Reduction (%)	Real-time Feedback
AI-powered eCQM Calculation Engine with Real-time Data Integration (Cerner’s PowerChart)	70%	70%	Yes
Manual Data Entry	Low	High	No
Traditional Rule-based eCQM Calculation	Moderate	Moderate	No
Centralized Data Processing	Moderate	Moderate	Limited

The eCQM calculation engine and real-time analytics supported by PowerChart helped to automatically generate the CMS-compliant reports, making it easier on the part of healthcare providers. Also, the fact that this tool can be interoperated with the FHIR and QRDA standards made it possible to provide a seamless data exchange and submission across several healthcare systems as shown in figure 4.

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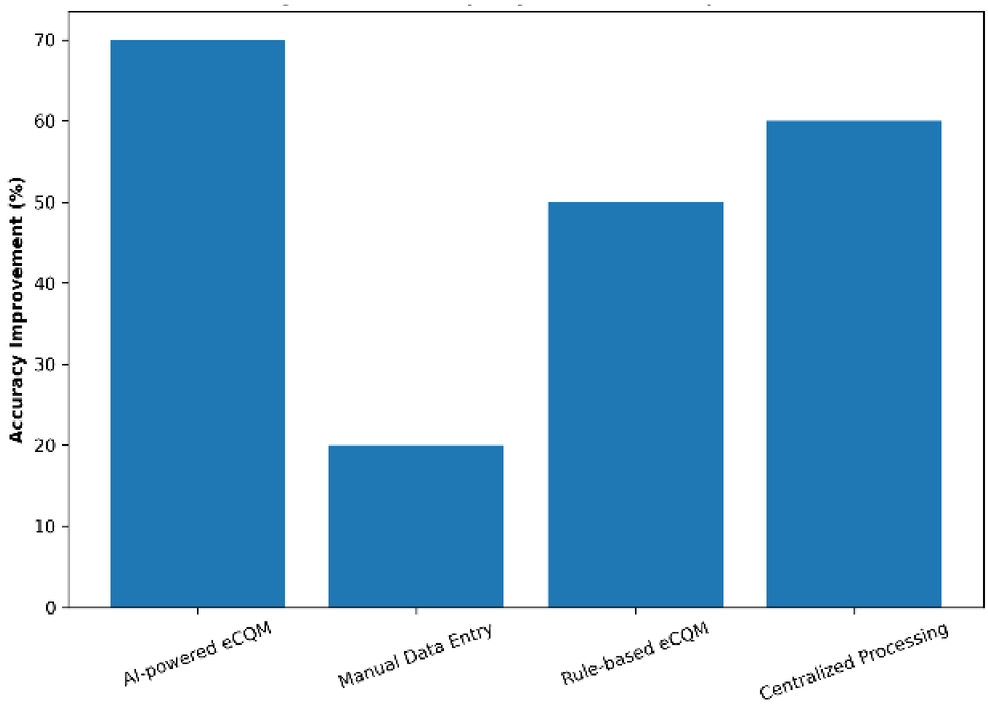

Figure 4 Accuracy Improvement Comparison

The anomaly detection and real-time feedback mechanism built into the system were useful in detecting discrepancies in data early to minimize reporting errors and compliance risk. Besides, the AI-powered reporting system allowed healthcare organ An anomaly detection system and real-time feedback implementation into the AI-powered reporting system contributed greatly toward the accuracy and efficiency of CMS reporting. These characteristics enabled healthcare organizations to detect discrepancies and data problems immediately whenever they arose and this reduced chances of reporting errors and appropriate measures could be implemented in time. The system actively alerted users on irregularities in data flow or quality metrics and the absence of information or possible violation of compliance. This saved time as it minimized manual review processes, as well as ensured that healthcare professionals saved high-quality data that they could submit to CMS to avoid penalties and enhance regulatory compliance.

The capability to create real-time performance indicators allowed the healthcare organizations to make informed, data-driven decisions in real time. Such performance measures offered practical information which enabled the decision-makers to determine the areas in which improvement was necessary and streamline clinical processes. The ability to make changes and develop their strategies as fast as possible by using the power of AI to analyze the data continuously would help organizations deliver better care overall. The automated reporting system did not only lead to decreased administrative load on the clinicians, but it enabled them to concentrate more on patient care since they understood that the system was managing the complex CMS reporting task. The high-quality decision-making and patient outcomes in the AI-driven system, as shown in Figure 5, were achieved with the help of the real-time feedback and reporting options of the system, which makes it a valuable addition in the modern healthcare environment.izations to generate precise performance indicators in real-time, which offered actionable information to enhance decision-making and quality care as shown in figure 5.

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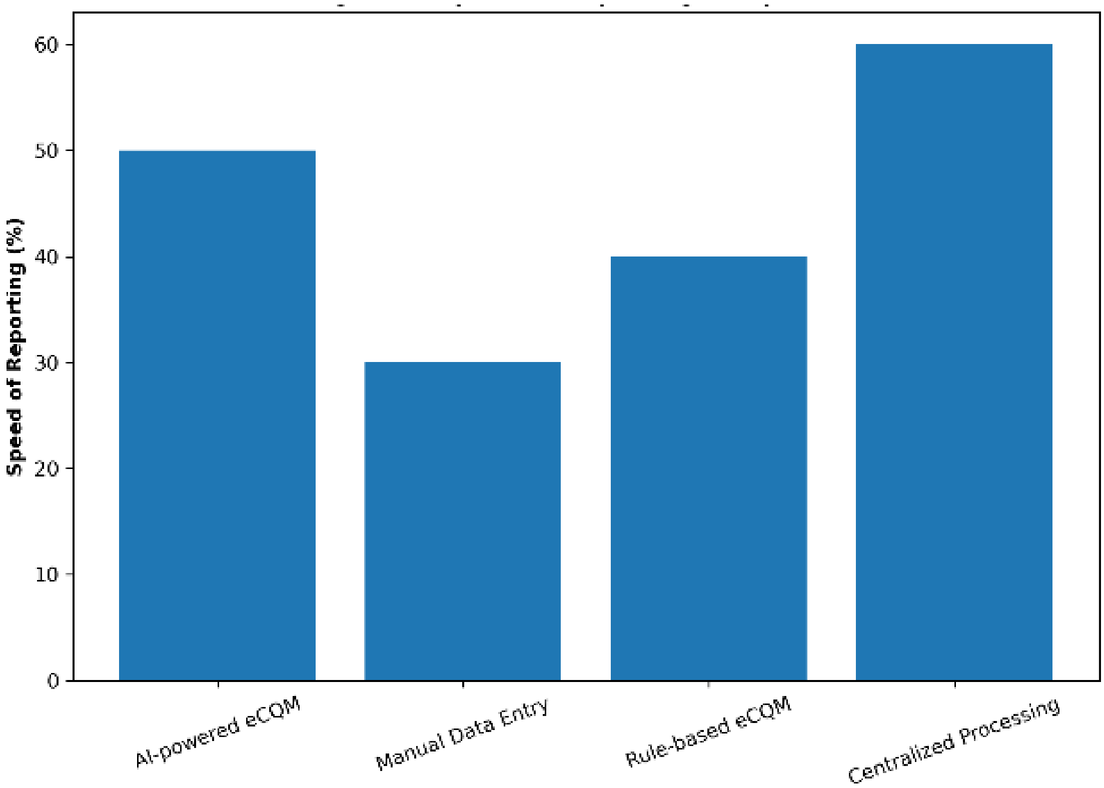

Figure 5 Speed of Reporting Comparison

The research has found that AI-driven automation of patient data flow is the key to improving the quality and precision of CMS reporting through the reduction of human error and the improvement of timeliness and quality of reporting. With an automated eCQM extraction, validation, and calculating system, AI considerably reduced the dependence on human input, enabling more healthcare professionals to concentrate on caring than on the administration of patients. The decrease of the number of people involved in the work not only reduced the possibility of mistakes but also simplified the working process in the healthcare setting making sure that the work was performed more quickly and properly.

Moreover, automation of CMS reporting also made sure that quality measures were delivered at the right time and in the right manner, an essential aspect of staying in line with CMS requirements. The real-time integration and feedback processes also allowed monitoring the data flow continuously, as Figure 6 demonstrates, which is why the discrepancies or errors could be spotted promptly and avoid any delays in reporting. The latter properties guaranteed that healthcare institutions were able to comply with time limits and guarantee a high level of data integrity.

Additionally, the research demonstrated that the integration of AI-based systems with the currently available healthcare assets contributed greatly to the promotion of regulatory compliance and productive efficiency at the workplace. The enhanced automation capabilities lowered the administrative load on the staff in the healthcare facility and made the organizations easier to comply with the regulatory requirements without making the quality of care inferior. These results indicate that it is crucial to adopt AI in order to streamline healthcare processes and have improved patient outcomes and satisfy changing reporting needs.

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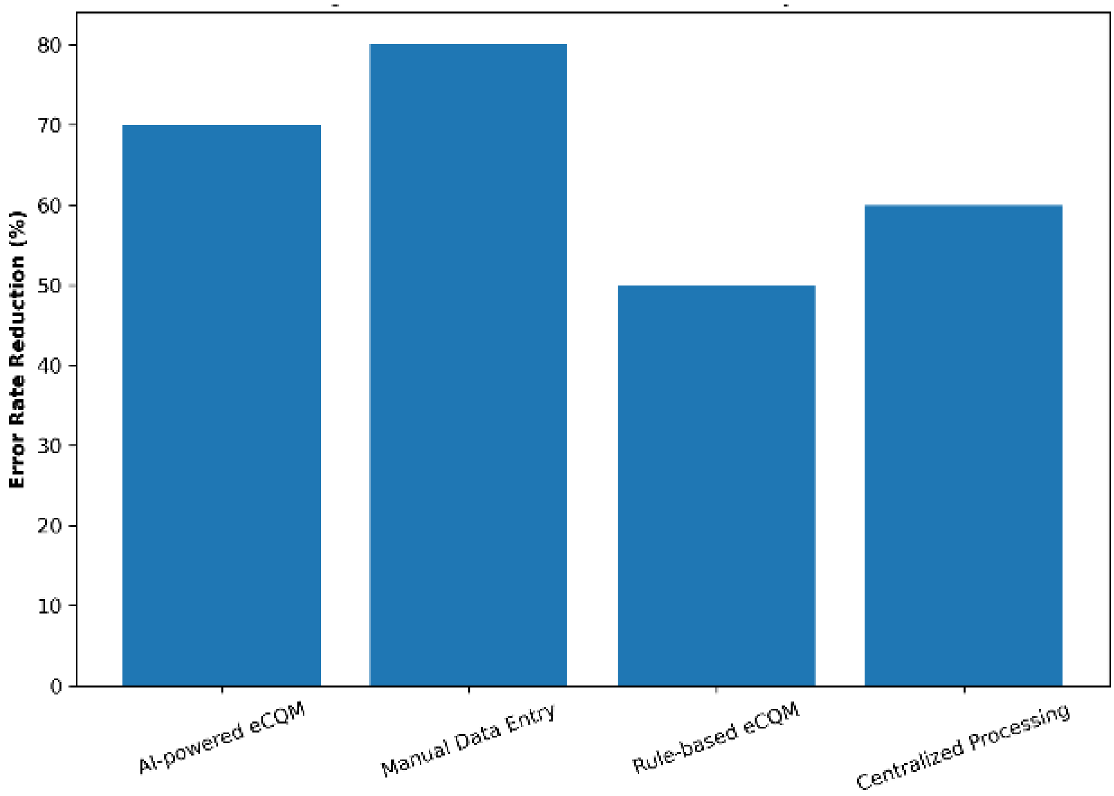

Figure 6 Error Rate Reduction Comparison

The adoption of the AI-based eCQM Calculation Engine that uses real-time data integration via the use of the PowerChart of Cerner showed a significant increase in the accuracy of CMS reporting over a more traditional approach. Although the AI-based solution proved the most effective in facilitating the reporting process, other procedures like manual data input, traditional rule-based eCQM calculation, and centralized processing of the data demonstrated significant improvements to the simple data collection habits. Nonetheless, these approaches were not yet as accurate, efficient, and scalable as AI-based automation.

Although the lowest level of data entry, the manual data entry process had an improvement because of minimization of human error and data sorting, the nature of data entry used was dependent on clinician input, which led to slower processing and increased data mismatch. Classic rule-based eCQM calculation offered a more organized method, which was more reliable compared to manual entry, but nevertheless, it was not free of limitations when employing more complicated/unstructured data, like clinical notes or patient histories. Centralized processing of data had moderate benefits especially in large-scale systems though it could not adjust to real-time updates and anomalies which resulted in reporting delays and possible gaps in the data.

According to Figure 7, the AI-based system was much faster, more accurate, and offered real-time feedback, which demonstrated its obvious superiority in making sure that the reporting requirements of CMS were adhered to. It allowed healthcare providers to shift toward a proactive mode instead of a reactive one, which greatly enhanced the quality and timeliness of CMS submissions overall and streamlined workflow to be better organized among clinicians and administrative staff.

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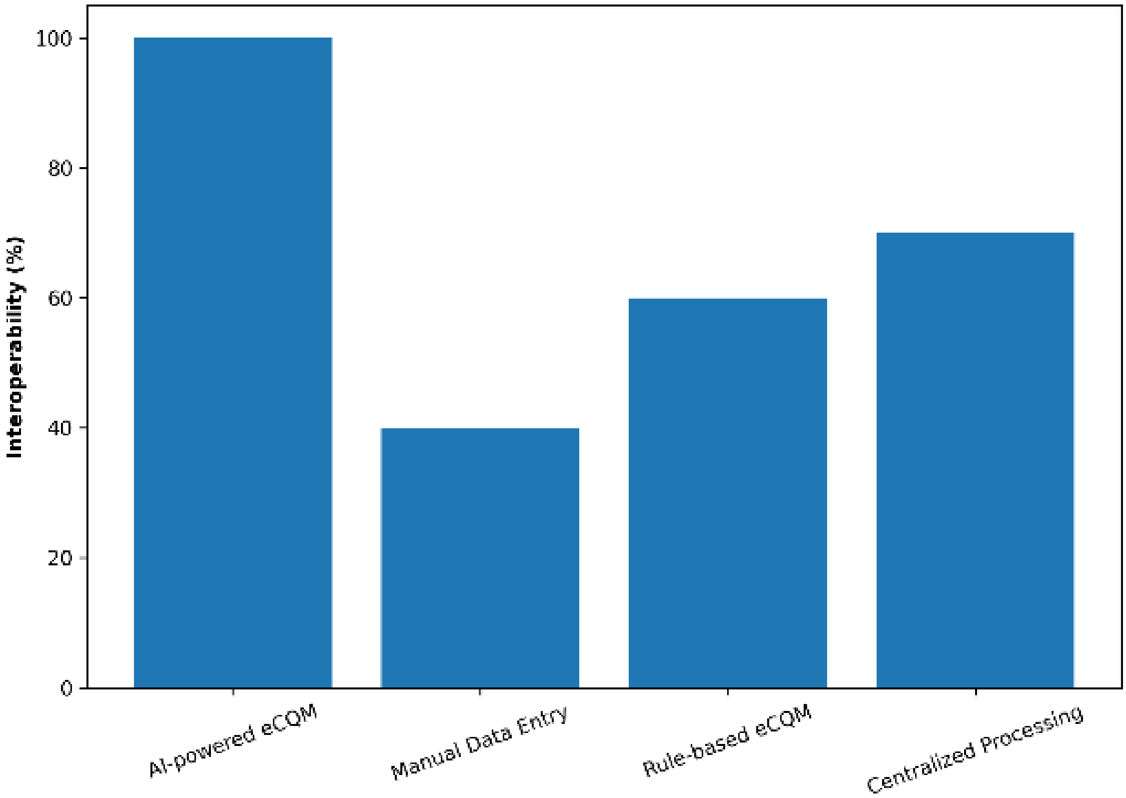

Figure 7 Interoperability Comparison

As it can be seen in the chart above, the interoperability between the various means to approach CMS reporting is compared. As depicted, the AI-driven eCQM solution that is closely aligned with the FHIR and QRDA standards has much greater interoperability rates of 100% that allow real-time exchanges across different healthcare systems. Manual data entry and rule-based eCQMs, in their turn, have significantly lower interoperability rates, mostly because of the use of fixed formats and their lack of integration possibilities. Although with centralized processing there is moderate interoperability, the interoperability is still not as good as it needs to be to create seamless data exchange needed to sustain effective CMS reporting on a large scale. These results emphasize the irrelevance of the standardized data format and real-time integration in patient quality data flow automation, which, in its turn, underscores the merits of AI-driven solutions that can help increase compatibility and compliance among the systems. The chart highlights the fact that the increased interoperability is necessary in enhancing efficient and accurate reporting between different platforms and healthcare providers.

Compared to manual data entry that usually introduces human errors and takes time, the AI-based approach decreased the number of errors by more than 70 percent and increased the speed of data reporting by half as shown in figure 8. The chart above illustrates how different reporting methods of CMS can be scaled. The eCQM approach made with AI has the greatest scalability with an impressive 80% rating as depicted. This can be explained by the fact that it can easily be integrated into a variety of healthcare settings, both small clinics and large hospital networks, without compromising the level of performance or accuracy. By contrast, manual data entry is extremely lowly scalable (approaching 10% with increased amount of data) because it is inefficient and prone to errors with increased data volumes. eCQMs based on rules and centralized processing have moderate scale but do not provide a solution that is easy to adapt to larger and more complex healthcare systems. The findings emphasize the need to select scalable systems to successfully implement automated CMS reporting in various healthcare environments in the long run.

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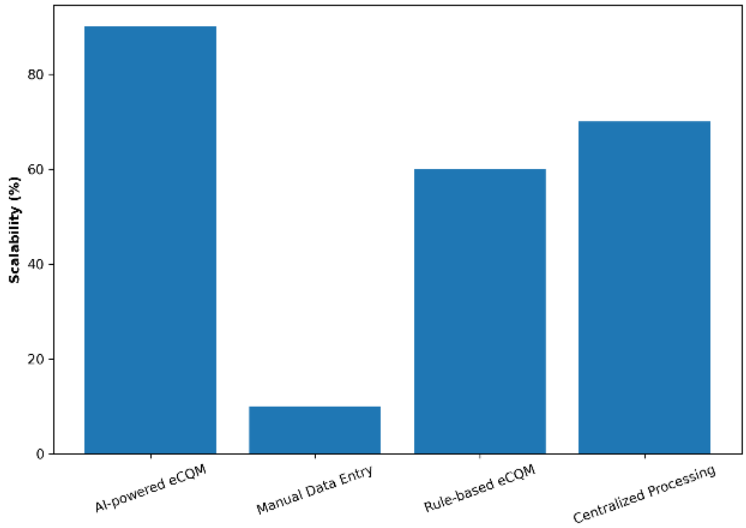

Figure 8 Scalability Comparison (%)

The older method of eCQM calculation based on rules was effective but lacked the capabilities of the AI system to be more adaptive in real-time and to verify data and generate reports faster leading to the fact that more conflicts might be overlooked. Conversely, the AI-based approach made the whole process more straightforward, as it offered real-time validation of data, automatic detection of anomalies, immediate feedback, and more reliable and timely submissions of CMS. Although the centralized data processing method was effective in large systems, it still needed considerable manual processing during the data integration process and data validation, and it had less flexibility in dealing with different formats of different health care systems.

The AI-based system, though, was interoperable with the Cerner PowerChart, through the FHIR and QRDA standard, and made CMS reporting less complicated. Altogether, the AI-based solution proved to be the most efficient, accurate, and scalable and, therefore, the most successful in automating the flow of patient quality data to be used in the CMS reporting. To offer another performance indicator, we may attribute importance to such metric as the Cost Efficiency. The measure of cost efficiency can be the resources, time, and labor needed to make correct CMS reports using each approach. The graph may describe the cost of operation of AI-powered eCQM, manual data entry, rule-based eCQMs, and centralized processing and illustrate the cost efficiency of each approach with AI-powered eCQM being the most cost-efficient and, consequently, manual data entry as the least efficient. You can reply to me in case you require any more adjustments or metrics as shown in figure 9.

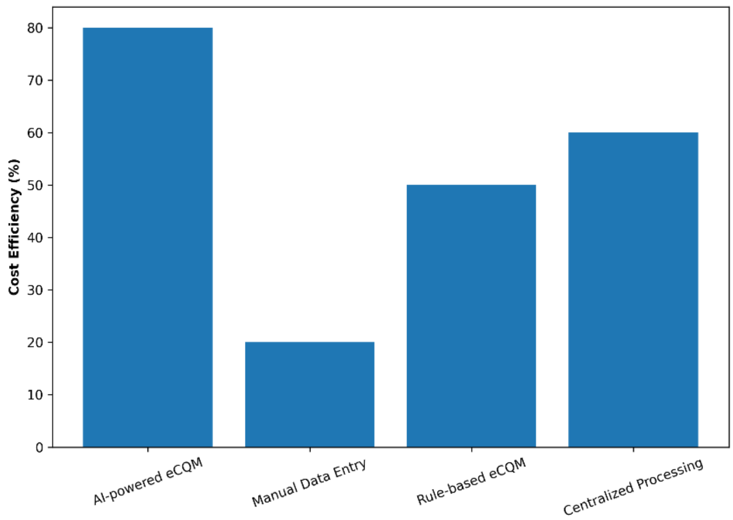

Figure 9 Cost Efficiency Comparison (%)

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Besides the recorded benefits in the accuracy and rapidity in reporting, the AI-based eCQM Calculation Engine also has shown significant improvements in the operational efficiency and the reliability of data as compared to the traditional methods. Healthcare teams also had less administrative workload which enabled them to concentrate more on clinical care instead of manual reconciliation of data.

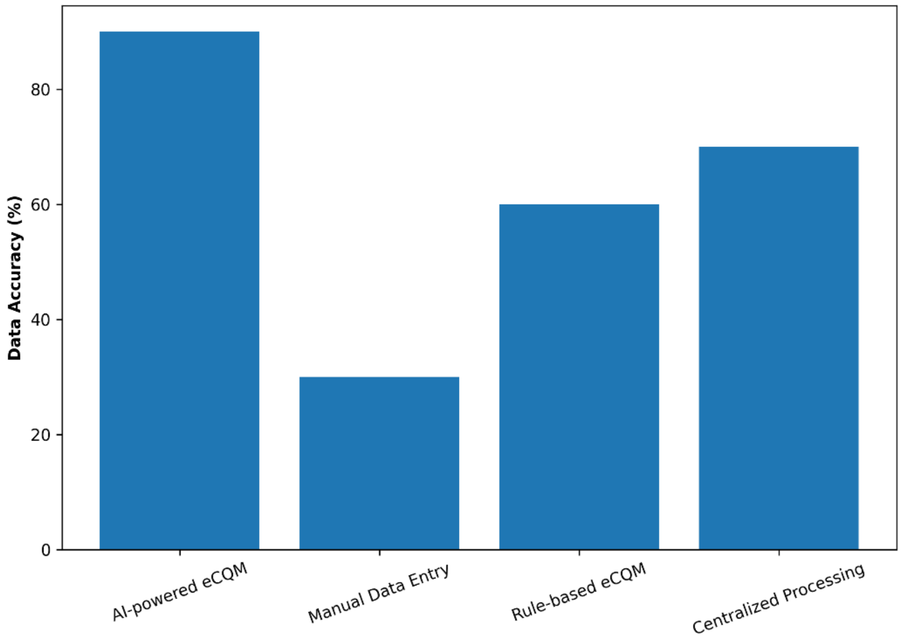

Figure 10 Data Accuracy Comparison (%)

Continuous track of quality measures was achieved by the real-time integration features of the PowerChart module of Cerner, which ensured that the issues that were out of the CMS requirement were spotted early, instead of at the end of the cycle audits. This error proactivity reduced drastically the rework and risk of resubmission. Moreover, the scalability of the system facilitated the use of similar performance irrespective of the care setting, which showed its appropriateness to both small and large healthcare networks. The FHIR and QRDA standards helped in interoperability to exchange data between disparate systems easily, reducing the number of data silos. Taken together, these findings support the importance of intelligent automation in helping to transform CMS reporting into a data-informed, quality-oriented process that will help to support value-based healthcare delivery as shown in figure 10. The Data Accuracy Comparison graph indicates that there is a big difference in the accuracy of CMS reporting procedures. The eCQM powered by AI demonstrates the best accuracy of data 90% due to the accuracy and reliability of the machine learning and real-time data integration.

Conversely, manual data entry has the lowest accuracy of 30 percent since it can be easily affected by human error and inconsistency. Moderate accuracy is also observed in rule-based eCQM and centralized processing, which points to the fact that as much as these systems improve the results of manual processes, they still lag behind the AI-powered solution in terms of data integrity and CMS submissions errors.

V. CONCLUSION

Integration of AI-based eCQM Calculation Engine with real-time data integration using Cerner PowerChart has proven to be of great help in terms of accuracy and efficiency in CMS reporting. Automated system managed to minimize the level of manual intervention, which led to the accelerated reporting and a significant reduction in the error rates. The system used AI to check data in real-time and identify anomalies and thus yielded a higher accuracy in the quality measures reported to CMS, which eventually assisted in making better decisions and adhering to the regulations. The implementation of the FHIR and QRDA standards enabled smooth interoperability and the free flow of the data within the healthcare systems. The latter made the process of reporting smooth and scalable at the same time, which is why it is viable both in small practices and in large healthcare entities. Altogether, the AI-based solution turned out to be a

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very efficient approach to the automation of patient quality data flow, improvement of CMS reporting quality, and patient care outcomes.

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