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Using Gen AI and LLMs for Process Automation in Healthcare

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Abstract

The development of Electronic Medical Record (EMR) systems has improved the summarization features of these systems. Research has been well-positioned on how Large Language Models can be deployed alongside EMR systems to create efficient summarizations. This research paper focuses on using Natural Language and thoroughly analyzes the integration of UiPath and GenAI into EMR systems. A hospital provider often interacts with various systems during patient care, and employees must deal with humongous data from various applications. Sometimes, the sheer nature of the volume of applications involved and the vast data from those applications make the analysis daunting. Effective summarization of unstructured patient data in Electronic Medical Record (EMR) systems is vital for accuracy in diagnosis and efficiency in patient care. But, due to the issues mentioned, clinicians often face an overload of information and time constraints. This research paper focuses on various functions in hospital operations and how data summarization and data analysis can effectively improve care. The current functionality of EMR systems in summarizing the data is mentioned. Also, the importance of patient summaries in clinical data is discussed, and this research paper also provides a methodology on the usage and integration of UiPath and Gen AI activities for improving patient care.

Keywords: Electronic Medical Records (EMR), Natural Language Processing (NLP), UiPath, GenAI, Action Center, LLMs (Large Language Models),Robotic Process Automation, OCR

1. Introduction:

[1] Although there’s wide variation in specialties, critical care clinicians spend significant time on EMR systems- an average of 5.8 hours outside of patient care, and a significant portion of that time is spent outside of clinicians' working hours. This finding is part of a study of more than 2,00,000 physicians. This study shows how clinicians are burdened with clerical work at a time when their time could be used to advance the betterment of patient care and improve time spent with each patient.[2]According to a study, the amount of time that a physician spends on Electronic Medical Records is a concern for USA’s hospitals. Healthcare system. As there would be potentially large implications of overhead costs and less patient interaction, particularly for the physicians whose work is mostly cognitive, the study's findings raise a concern and pose a need to document the time physicians spend on accessing EMR-related functions. The study is descriptive and USA-based, and the setting includes adult, nonsurgical, and ambulatory functions using Cerner Millennium EMR. The focus group comprises155,000 U.S. physicians and data from 100 million patient interactions from 417 health systems. According to the

study, physicians spent an average of 16 minutes and 14 seconds per encounter using EHRs, with chart review (33%), documentation (24%), and ordering (17%) functions accounting for most of the time. Also, this time distribution on EMRs varies by specialty, with some physicians spending more time. This presents an opportunity to optimize the systems and processes. Effective summarization of unstructured patient data from EMRs is crucial for effective hospital operations, yet clinicians often find it difficult to navigate through information overload and time constraints.[3]Clinical summary is the process of distilling medical information from multiple sources, such as biomedical books, literature, and patient data. Natural language processing (NLP) can determine illnesses or patient information from clinical free-text. Hence, due to the above-discussed issues and many other challenges that entail clinical data summarization, it is necessary to perform more research in this arena and enable physicians to focus more on patient care instead of burdening them with clerical data.

Some areas in hospitals where clinical summarization can be applied include patient data summarization of the EMR systems, including Epic and Cerner, email triage, critical monitoring and care, and patient feedback analysis. There be many other areas where effective summarization and analysis of patient data can be performed, but this research paper focuses on the mentioned areas. This paper mentions summarizing patient data by considering various stages during visits from visit to discharge. The current functionalities of summarization in EMR systems, such as Epic and Cerner, and the effective UiPath and GenAI combination are mentioned to resolve some of the challenges, such as interoperability and inconsistency in data. The issue of strained staff due to monitoring of huge incoming emails, and inefficiencies related to categorization and resolution are mentioned. Additionally, the issue of patient or family feedback analysis is addressed. This research paper mentions how these challenges can be resolved by using a combination of UiPath and GenAI.

2. Patient Data Summaries:

The Patient could have various notes written throughout various stages during a visit to a hospital facility. From admission to discharge, there could be various stages in which various departments will write notes. Skimming through multiple documents, including handwritten documents, digital files, and reports, is a time-consuming and administratively tiresome process, inflicting overhead on the operations team when they could instead focus on better patient care. UiPath Bot can be configured to summarize the data from various documents, including structured or unstructured, digital or handwritten documents. There are various stages where the summarization of clinical information is needed in a hospital. The most common stage would be during the discharge stage, so clinicians can prepare a clean, detailed discharge letter. The other case is during a specialist’s referral. Once a patient is referred to a specialist, instead of presenting a series of documentation to the specialist, if a summarized case could be presented, it would ease the process, eliminating unnecessary overhead and focusing on the actual diagnosis or next course of action. This would also increase the doctor's time with patients to know more about them. Also, during care transitions when transferring a patient from the Emergency room to the general ward, summarization of previous notes would make the shifting process smoother. Issues related to clinical monitoring and automation of clinical documentation are also mentioned.

Test Data:

Patient Name: Mr. Robert K.

Age: 58

Chief Complaint: Increased thirst, fatigue, frequent urination, blurred vision.

Clinical Notes:

The patient presents with classic symptoms of Type 2 Diabetes Mellitus. HbA1c is elevated at 9.1%. Past medical history includes hypertension and obesity (BMI: 34). There are early signs of diabetic neuropathy noted in foot exam, including tingling and reduced sensation. Fundoscopy indicates early diabetic retinopathy. Lipid panel shows elevated triglycerides.

Below is the diagnosis information:

Treatment Plan:

- Prescribed Metformin 1000mg BID

- Advised on diet modifications (low sugar, low carb)

- Referred to endocrinologist and nutritionist

- Scheduled follow-up in 4 weeks with repeat blood tests

Patient Name: Ms. Angela P.

Age: 72

Chief Complaint: Difficulty breathing, wheezing, and fatigue for past 3 days.

Clinical Notes:

Admitted with acute exacerbation of COPD. History of smoking (45 pack-years). On physical exam, diminished breath sounds bilaterally with wheezing. SpO2 was 88% on room air. Chest X-ray shows hyperinflation and signs of chronic bronchitis. ABG confirms respiratory acidosis. Patient placed on BiPAP and started on IV methylprednisolone and nebulized albuterol/ipratropium.

Treatment Plan:

- Continue oxygen therapy and monitor ABG

- Pulmonary rehab referral after discharge

- Smoking cessation counseling

- Start tiotropium once stabilized

After using Gen AI activity called Summarize Text, the output will be as below

"Mr. Robert K., 58, is experiencing symptoms indicative of Type 2 Diabetes Mellitus, including increased thirst, fatigue, frequent urination, and blurred vision. Clinical tests show an elevated HbA1c of 9.1%. His medical history reveals hypertension and obesity with a BMI of 34. Early diabetic neuropathy is observed in the foot exam with tingling and reduced sensation, and fundoscopy shows early diabetic retinopathy. Additionally, his lipid panel indicates high triglycerides. The treatment plan involves prescribing Metformin 1000mg twice daily, recommending dietary modifications to reduce sugar and carbohydrates, and referring him to an endocrinologist and a nutritionist. A follow-up is scheduled for 4 weeks to repeat blood tests."

[1] Using the Settings icon in the Summarize Text activity establishes the connection between the studio and the integration service, letting the bot use the LLM model to perform the actions. The output contains two variables, one of type string and the other of type summarize_Create. Enter Text to Summarize, Number of Summary words, and Summary Format as inputs. Several summary words set the word limit for the synopsis of the given text.Using Natural Language Processing, the LLM model finds the proper length if not supplied, and Int32-type input is supported in this field. Summary Format options are Paragraph, Bulleted List, Numbered List, Outline, Tabular, and Chronological. Workflow can be designed in such a way that the information will be retrieved using data extraction from documents, which are digital or non-digital, and passed as input to the activity Summarize Text. The output from this activity will be used as a summarized text. It can be captured in electronic medical record systems, letting clinicians or other staff use or send the information when needed. This saves physicians time and reduces handoff errors.

Summarizing clinical data has far-reaching implications for patient care, which is one reason for physician burnout. Physicians can focus on improving patient care by letting the bot handle this tedious and often manual task. It is important to note the distinction for time spent on different care types on EMR (Electronic Medical Record) systems.In many cases, more time is needed; some include specialty treatment, including psychiatry, neurology, or rheumatology. The other type of care that may have huge data to summarize is inpatient care, as there will be daily notes, summaries while shifting between different wards, discharge summaries, order entry, and medical reconciliation.[2]Effectively summarizing unstructured patient data is essential for better patient care and optimizing clinicians' time. Different hospitals use different electronic medical record systems (EMR), and some of the systems lack AI/ML integration, which is crucial for summarization. Even if some of the summarization capabilities exist for some EMR systems, it is essential to integrate Robotic Process Automation (RPA) to customize the summarization rather than relying on the inbuilt summarization provided by EMR systems.There is no standardization of summarization for EMR vendors, as different EMR vendors use different systems. Some of the EMR systems, their summarization capabilities, and the use case of RPA integration into each system are further discussed in this paper.

a) Epic Systems:

Epic is one of the most widely used electronic medical record systems, and its built-in summarization tools are not entirely customizable and mostly rely on predefined templates. The chart review feature in Epic systems provides a longitudinal view of patient records. This view includes interactive tabs for visits, labs, imaging, meds, procedures, and notes. Chart view aggregates the patient's data from all past visits. In chronic diseases and long-term care, doctors must scroll through humongous information and review various sections to understand the patient's condition, history, and diagnosis. Note reader AI uses Natural Language Processing (NLP) to suggest diagnoses and relevant information from clinical notes. It detects certain conditions based on keywords mentioned in the clinical notes. Typing. dmhx inserts "Patient has a history of diabetes and typing @lastbp auto-inserts the patient’s last blood pressure value. Static templates and keyword-based logic don’t fall under the proper use of Artificial Intelligence capabilities in text summarization. Also, it cannot effectively summarize across multiple sources of unstructured text. There is also a feature named Health Maintenance and Snapshot Overview in Epic systems. It summarizes key patient information on the screen regarding vitals, allergies, and lab results. Health maintenance features track whether tests recommended as part of preventive care are performed. The limitation is that this feature focuses more on preventive care than contextual summaries of patient journeys or critical events. Auto-generated reports are available for discharge summaries, progress notes, and hand-off reports, but depend on predefined templates and fields from the Epic system. The limitation is that it lacks customized narrative summaries across patient journeys and is unsuited for external document summarization or patient handovers based on each unique case.

Hence, even with the usage of Epic and its features for summarization based on certain contexts, there’s still a strong case for enhancing the capability for customized summarization of clinical data using a combination of Robotic Process Automation and GenAI. It is particularly helpful for hospitals dealing with document overload, clinical burnout, and poor data interoperability. Using UiPath and GenAI, documents of lab results and consultant notes can be read and routed for summarization. Also, documents from Epic systems can be read, and using the Summarize Text of UiPath’s activity, the information can be summarized by leveraging the in-built NLP features. Once the doctor reviews the AI-generated summary through Action Center, approval or denial action can be performed. One example of this use case is summarizing complex oncology cases for specialist referrals. Robot retrieves the information related to lab reports and external consult notes from Epic for the past few visits, utilizes OCR and Summarize Text to generate a clinical summary, and submits it to UiPath Action Center for the doctor to approve or reject. Upon approval, the bot sends a summary to a referred oncologist and uploads it to the patient’s Epic chart. This adds huge value as a custom narrative tailored for each use case can be generated and stored in the system, human-in-the-loop validation can be performed, and manual summarization time can be reduced by 60 to 80%. As Epic EMRs’ built-in tools offer foundational summarization but lack the adaptability and intelligence required for comprehensive narrative generation across structured and unstructured data, integrating UiPath RPA and GenAI activities, hospitals can enable smarter, faster, and more clinician-friendly summarization workflows that elevate both care quality and operational efficiency. As mentioned in the Figure 1- Visio Representation of end-to-end Text Summarization Process in Epic System Once the UiPath robot is triggered, it retrieves the documents to read and scans them. Some other use cases include summarizing multiple clinical notes across patient visits. Use UI automation to extract visit information and apply Gen AI to generate a high-level, summarized text. Using UiPath and Gen AI, discharge summaries from multiple sections and periodic summary reports can also be summarized. Schedule unattended bots to extract EMR data → summarize → email to care coordinators/physicians.

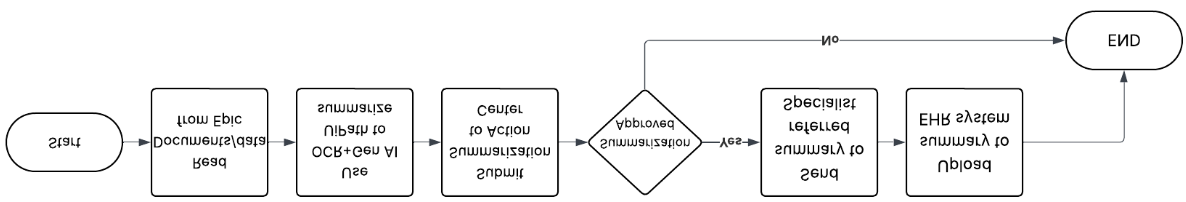

Figure 1- Visio Representation of end-to-end Text Summarization Process in Epic System

b) Cerner (Oracle Health):

Cerner, now part of Oracle Health, is another leading Electronic Health Record platform widely used by hospitals worldwide. Like Epic, it provides tools for document summarization but faces similar limitations when it comes to unstructured data and deriving intelligent narration from it. By utilizing Power Chart, which helps view a patient's history and clinical context, the Dynamic Documentation feature enables data to be automatically added to the notes as doctors type. However, it doesn't summarize longitudinal data, though it exists for viewing. For example, the hemoglobin value for the last 3 years will be displayed in different sections, but summarization will not be provided. UiPath Bot logs in to Cerner, navigates through multiple visit notes, lab results, and specialist summaries, summarizes text using Gen AI, generates an Action Center task, accepts validation by a doctor, and uploads the summary to Cerner. The sample summary would be 'The patient has experienced persistent hypertension unresponsive to first-line therapy, requiring a medication switch in March. The cardiologist suggested adding a beta-blocker based on rising pulse rate trends.' Some of the summaries include past visit history, which includes notes from past encounters, diagnoses, and treatments; Lab trends, which include data from tests over 6 months; medication changes, which signifies what medications are used, stopped, or restarted; and specialist opinions, which contains data provided by specialists over multiple visits.

3. Email Triage:

Hospitals receive hundreds of emails from patients, insurance providers, Labs, or internal staff daily. The requests are often related to insurance verification, appointment rescheduling, test results requests, prescription refills, or billing disputes. These emails are often routed to the email inboxes of a hospital or individual departments. Once the staff members read emails, they categorize them and assign them to the department concerned. This manual and fragmented process leads to delays and missed communications. This is often an intense and error-prone task. The combination of UiPath Communications Mining and Natural Language Processing through Gen AI activities takes care of reading and understanding the email content, classifying the intent, extracting important details, and routing the email to the concerned department. Optionally, urgent emails can be classified using NLP tone detection. This eliminates manual sorting of emails, creates faster responses, and increases productivity. UiPath Bot continuously monitors, using Outlook activities and a shared mailbox, extracts the subject, attachment, and body, uses read email and save attachments, and classifies text using GenAI's Classify Text and various other activities. It classifies the email into categories such as appointment, insurance, urgent clinical, etc. The bot then generates a short summary describing the contents of the email. In the next step, entity information such as patient name, MRN, Date, Department, and Doctor name is extracted. Bot uses Regex or GenAI activities to extract information related to entities. As a next step, Bot routes the email to the concerned team based on extracted data and classification. Also, if an email is marked as urgent, a ticket can be created in the action center so that the team can review it constantly and address urgent issues on a priority basis. For example, if the email text is 'I'd like to cancel my appointment on 14th with Dr. James, it'll be classified as appointment scheduling and routed to the front desk/scheduling department. If the email text is 'patient covered under Aetna denied pre-auth for MRI. If you need help, the email will be routed to pre-auth or the revenue cycle team after being classified as an insurance issue. Traditional rule-based activities involving Regex classify the email and its content but fail to understand the context and tone. The Bot can understand the context and intent using GenAI activities, even in an unstructured form. It can assign confidence scores to each category, providing summarization capabilities and sentiment analysis for enhanced decision making. In case of low confidence predictions or sensitive content, integration of UiPath Action Center can be done, and it can be assigned for manual review.

Manual triage of emails results in delayed and missed responses. Much of the staff's time will be spent reading and analyzing the emails, leading to inconsistent routing and prioritization. As the volume increases, the operations will be strained, leading to inefficiencies. Hospitals already deal with burnout among employees due to the huge influx of patients in certain areas, and this administrative task will further strain the employees.[3] In the hospital, every minute counts, whether in patient care, administrative duties, or daily activities. The number of emails for a hospital can overwhelm the staff, creating overhead and inefficiencies in operations. All the staff would usually be occupied and working at maximum capacity. Assigning these kinds of administrative tasks can be a burden to critical patient care operations. The doctor's email inbox may be inundated with emails from patients, vendors, nurses, lab technicians, and administrative staff. Without an effective way to handle these emails, crucial details may be overlooked, potentially compromising patient care. In hospital settings, critical emails, such as patient referrals, lab results, or appointment confirmations, can often go to the spam folder, leading to communication misses and risk for patient care. This is often due to stringent spam filters that depend on configured rules and can result from various factors, including email content, sender reputation, and spam filter configurations. Using Machine Learning enhances email filtering accuracy. Content-based filtering utilizes naïve Bayes and support vector machines to analyze email content and distinguish between legitimate messages and spam. Header analysis focuses on detecting anomalies without relying solely on content. Deep learning models use advanced models such as BERT (Bidirectional Encoder Representations from Transformers) for understanding the connotation of email, leading to accurate detection of the spam category. [4]It is also important to categorize and flag malicious emails and prevent false positives. This is done by applying a machine learning technique called deep learning to the emails. The system improves with data, and more efficiency can be seen as time progresses, with data being passed to the ML model frequently.[5]Anomalies in the email, such as phishing and spam, present security risks to organizations and individuals. Money can be lost, or sensitive data can be compromised. Relying on the email body and content to categorize spam emails is challenging. The research focuses on email header metadata. Features such as sender address, time zone inconsistencies, subject line anomalies, and message ID structure are extracted from headers. According to the research paper, 98% accuracy is achieved for header-based models distinguishing between normal and suspicious models. Also, email privacy is preserved as no content analysis will be made.This system can be integrated into hospital IT systems to prevent critical emails (like patient records or referrals) from being flagged as spam, using only metadata without violating HIPAA or data sensitivity rules. Hence, considering all the above-discussed factors, there is a need for email management.

4. Clinical Monitoring and Care:

During the primary stage, Adverse Drug reactions are captured and documented. Nurses and physicians record symptoms, new complaints, and responses to the medication. Early detection of adverse reactions is crucial as it prevents escalation and timely medication switching. Usually, doctors take notes of ADRs in their routine check-ups, which is often manual. The notes related to ADRs can be digitized and rewritten in a structured way into electronic medical record systems. This way, medication changes can be documented during discharge in case of an allergy or adverse reaction. This helps in avoiding further re-prescriptions of the problematic drug. Also, as part of regulatory reporting, these ADRs must be extracted from the electronic medical record systems and reported to drug safety authorities. In the *Figure 2- Input prompt*, Input provided to GenAI is presented, and in *Figure 3- Output of GenAI* The Output provided by GenAI is presented. The output of the GenAI activity Rewrite is presented. The inputs are the content to be rewritten, the instructions to be rewritten, and an example, which is a sample of rewritten content to identify style and tone. The output is rewritten content, and there's an option to set the limit for the number of words in the output.

"The patient, a 67-year-old male with a history of hypertension and Type 2 diabetes, was admitted for shortness of breath and dizziness. He had recently been started on Metoprolol for blood pressure management and Glipizide for glycemic control. Within 3 days of starting Metoprolol, he developed bradycardia and fatigue, which progressively worsened. The patient also complained of episodes of confusion and tremors, particularly after meals, which coincided with Glipizide administration.Furthermore, the patient was on Atorvastatin for lipid control. He reported experiencing muscle cramps and generalized weakness that began two weeks after initiating the drug. These symptoms improved after discontinuation. During his hospital stay, he was administered IV Ciprofloxacin for a suspected urinary tract infection. Shortly after administration, he developed itching and a diffuse erythematous rash over his chest and arms. The antibiotic was stopped, and he was switched to Ceftriaxone, which he tolerated well without further reactions. The care team was also notified about a past episode involving Amoxicillin, which had caused severe diarrhea and abdominal cramping six months ago. A medication reconciliation was completed and adverse reactions were documented in the patient's chart and pharmacy system.

Figure 2- Input prompt

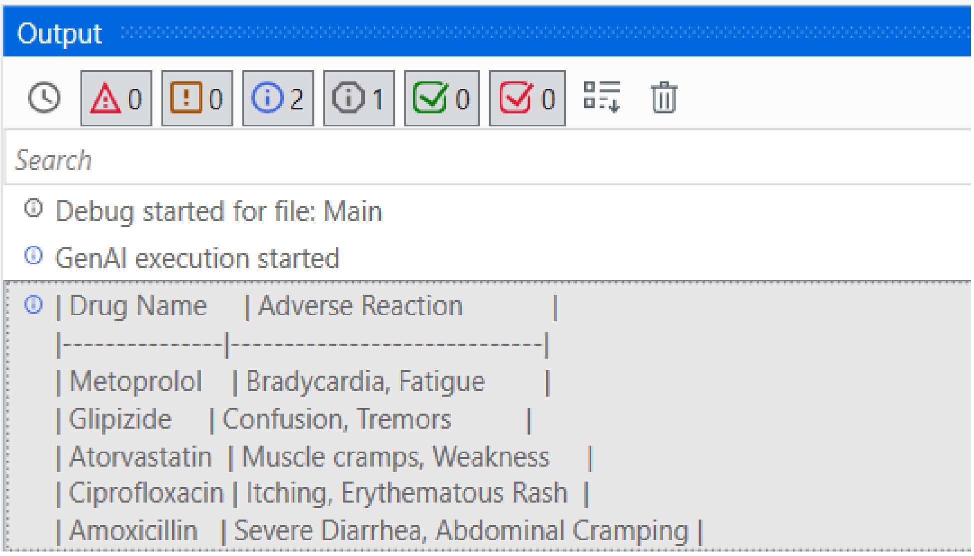

Figure 3- Output of GenAI

i.Real-time Patient Monitoring and Alerting:

Real-time clinical monitoring is crucial for managing terminally ill patients and patients who need constant monitoring. This is particularly helpful in emergency rooms and intensive care units. A combination of UiPath and GenAI can help automate continuous surveillance of the vitals of patients, lab results, and clinical indicators. Usually, this monitoring is performed manually, and trends of vitals are reviewed- a process that is both time-consuming and prone to human errors. In an ICU, UiPath Bot collects the temperature, blood pressure, and heart rate, among other parameters, every few minutes. The Gen AI model then compares the values obtained with the baseline values. If the model determines that values are over normal, it reflects a deteriorating trend, raising an alarm on the dashboard or via a mobile device. This reduces dependence on manual reviews, improves early detection, and provides intervention, delivering care on a priority basis for the patients who are at high risk. UiPath bots can be programmed to automatically extract patient vitals from EHR systems, telemetry devices, and wearable sensors at regular intervals.[6] Continuous monitoring of patients in intensive care generates vast amounts of data. Based on this data, clinicians in this practice often need to make split-second decisions, some of which can be life and death situations. It's challenging to discern the right course of action as humongous data will be available to decide. However, clinicians can utilize only a fraction of this available information. Even though many metrics and data points will be available, clinicians only focus on a few metrics to plan. These data points include history, physical examination, vital signs, and lab results. The vast amounts of data can work against the actual data,but when the clinician can discern based on experience, a decision will be taken regarding which data points will be used. There's a need to eliminate the unnecessary data points, and this is where clinical informatics can be very helpful. It can assist in promptly collecting and presenting pertinent data to physicians, aiding in patient identification and predicting worse outcomes.

Current challenges in clinical informatics are related to usability, interoperability, alert fatigue, privacy concerns, and high implementation costs. Most applications are diverse and have different user interfaces, creating burnout and frustration among the end-users. There is a lack of a proper mechanism to integrate various systems into Electronic Medical Record systems. Hence, clinicians often need to navigate multiple platforms to gather data related to the patient. Hence, improving interoperability is one of the important factors in improving clinical informatics that clinicians can use better. Alert fatigue is also one of the challenges, as clinicians can be overburdened with notifications. Protecting patient data and presenting the opportunity per HIPAA guidelines is also one of the key challenges. Moreover, the implementation and maintenance costs are huge, and small-scale organizations may be unable to afford them. Electronic Medical Record Systems often have complex, unintuitive interfaces, requiring multiple clicks and manual navigation to retrieve the data. This not only reduces the efficiency but may also create burnout. UiPath attended bots can automate EMR navigations, retrieve patient information from various applications and tabs, and populate the data, reducing the manual effort. Clinicians can type commands such as 'show last 3 blood gas results' and 'summarize ICU progress for past week, ' and GenAI delivers a summarized output. Multiple systems don't communicate effectively, leading to fragmented data. Using UiPath Bots, data can be aggregated from multiple systems. If each system is FHIR compliant, it would be relatively easy for the bot to make an API call and retrieve the data instead of navigating through the user interface (UI) as excessive alerts can take up crucial efforts of clinicians, train models on GEN AI-based contextual alert filtering to differentiate between urgent and non-urgent notifications. This way, if action center tasks are being used, create tasks only for urgent alerts, which can be classified based on Machine Learning confidence thresholds. To address the privacy or security issues, role-based access can be provided in the UiPath orchestrator, ensuring bots only access data they are authorized to access. Also, using an audit trail, every action can be traced. Also, use on-premises or private Azure/OpenAI endpoints with no data persistence to ensure secure NLP processing. UiPath bots don’t require additional infrastructure and can integrate with almost any system. Gen AI is a service that can be used, and the amount can be paid based on each call to the server. Also, when built once, the solution can be deployed across departments, addressing the concern of costs related to the implementation.

ii.Automation of Clinical Documentation:

Clinical documentation includes progress notes, operative summaries, updates to medication, and handover reports, among other use cases. This is one of the most time-consuming tasks for doctors, nurses, and therapists. Usually, clinicians spend around 40% of their time on documentation from Electronic Medical Record systems, and manually entering data increases the risk of errors, incomplete notes, and burnout. Critical care requires timely documentation to support faster decision-making and quicker handovers. The speed, accuracy, and usefulness of documentation in essential units of care can be significantly increased by hospitals by integrating UiPath's automation with Generative AI features (such as Summarize Text and Prompt GPT). UiPath Bot logs into the Electronic Medical Record system or connects to the application using FHIR component if it's enabled, extracts relevant information from various sections of the system using FHIR API, processes data using document understanding and OCR (Optical Character Recognition) if the document is scanned, and summarizes Text using GenAI activities. The generated prompt will then be sent to the action center for review, and upon approval, it’ll be uploaded into the EMR system through an API or UI based interface. Daily progress notes can be summarized based on data related to vitals, lab results, and nursing notes. Also, using this solution, discharge summaries can be created, post-surgery reports can be generated, and shift change briefs can be generated. This approach reduces the clinicians' time spent on documentation by up to 70%, significantly reduces the probability of typos, increases patient time with clinicians, and may create a good financial benefit for better compliance, improved billing, and quick reimbursements.[7] Using recordings from 14,606 patients who wore ECG devices for an average of 14 days, the researchers first had humans analyze the data. Severe arrhythmias were missed in 4.4% of patients by the human reviewers and in only 0.3% of patients by the AI. Lack of proper training to analyze the ambulatory ECGs leads to huge healthcare bottlenecks.

5. Patient Feedback Analysis:

The survey data must be considered for incorporating patients in fixing problems pertinent to bottlenecks for efficient and effective operations. This would be a game-changing improvement in patient care, letting patients receive care faster and more efficiently. Feedback can be classified as non-urgent and urgent feedback. Urgent needs to be addressed as quickly as possible. Staff can be acknowledged with gains for positive feedback. Systemic department issues can also be identified using the feedback analysis loop. Especially, in modern healthcare’s crucial wards such as ICUs (Intensive Care Units), patient and family feedback play a pivotal role in quality management, personalization of care, and hospital reputation management. Most feedback arrives in free text through various channels, including post-discharge surveys, emails, and social media. The nature of diverse reviews makes the review analysis difficult. Post-ICU surveys can help gather a summary or review after discharge and be captured using customer feedback forms. Nurses can digitally accept feedback based on interactions with the family of the patient. Alternatively, the family can request that the forms be filled out. There are certain digital channels where reviews can be extracted. Such reviews include data from websites, social media pages, apps, chatbot interactions, or web forms. Also, patient feedback can be collected after discharge through various digital forms. It is important to analyze what the forms would be to scrape reviews. For example, patients may use social media pages more for reviews than on websites. Hence, firstly, the importance and effectiveness of data should be analyzed, and data can be extracted from such systems. Most common challenges of analyzing feedback include manual processing that may take several days, low visibility as urgent issues may go unnoticed or not be prioritized accordingly, subjectivity and human bias in tagging/classification, and difficulty in identifying systemic issues or improvements.

An end-to-end automation that collects, classifies, summarizes, and escalates feedback using Bots can be configured to address these issues. Firstly, the bot can be connected to various systems such as Outlookmailbox, Google Forms, CRM, and EMR systems. If needed, handwritten feedback via OCR can extract information from handwritten text.Some themes can be identified for feedback upon using GenAI's Classify Text. The themes for feedback analysis include clinical care, communication, wait time, and staff behavior. The output will be tagged with a score and a category. Gen AI identifies the tone in the language: positive, neutral, or negative. Also, emotion can be detected – anger, content, and dissatisfaction. The bot generates a brief analysis per feedback row. An example would be a Patient who appreciated nursing support but expressed concern over communication from doctors. If the feedback is urgent, it can be routed as an action center task, an Outlook email item, or a support ticket. This kind of analysis, which is very structured and priority-based, would be more efficient than the manual review. Through this architecture, real-time feedback routing is possible,and complaints can be escalated within minutes, feedback can be categorized, classified, and quantified, providing data-driven improvements, higher patient satisfaction can be achieved, process improvements can be identified, and staff can be recognized for any tagged positive feedback.

6. Conclusion:

Integrating UiPath and Generative AI (Gen AI) activities with Electronic Medical Record Systems (EMR) offers a unique and viable solution for addressing longstanding operational issues in hospitals and improving the quality of patient care in an expedited pace that may be necessary in a medical setting. From clinical summarization and automatic document creationto focusing on real-time monitoring of patients, especially in critical care, and email triage, this research has demonstrated how Robotic Process Automation can reduce the burden on administrative staff, improve data availability and accessibility, and help in the efficient decision-making process about a case.Traditional EMR systems have some inherent capabilities for summarization and insights but cannot provide contextual intelligence. By leveraging UiPath's automation capabilities and GenAI activities such as “Summarize Text,” “Classify Text,” and “Prompt GPT,” hospitals can automate complex tasks like summarizing patient histories, flagging urgent feedback, and filtering adverse drug events—drastically reducing clinician effort and improving time-to-action. This paper also mentions the practical usage of generating intelligent summaries on a case by extracting data through various interrelated systems, usage of NLP, and extracting data from handwritten and digital documents, highlighting the potential for process improvement in these functions and presenting the use case for a faster handoff process in critical care functions. With secure, role-based automation, healthcare information management systems can stay HIPAA compliant and expand digital capabilities, scalable and cost-effectively. Overall, the combination of RPA and GenAI enables IT capability enhancement and drives processes strategically, reducing burnout, streamlining workflows, and humanizing care in a data-overloaded healthcare environment. As this integration matures, it has the potential to reshape clinical informatics into a proactive, intelligent, and patient-centric discipline.

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