International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 6, 2025
https://theaspd.com/index.php

Systematic Review Identification of Methods to Find Medication Errors and Poor Adherence

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ABSTRACT
Patient Health is the foremost responsibility for any provider or hospital. If there is any lack of providing consent to those information and challenges in updating the treatment plan in the right way leads to serious problems in patient health. Lack of proper system in capturing the human made errors leads to the misinterpretation of data. Although all time of traditional methods of taking prescriptions and capturing the results of individual patient information is crucial as an outmost responsibility. Lot of medical data is captured in traditional methods like handwritten, system entry. If these are misinterpreted or incorrectly captured, then it leads to serious troubles for the patients. We found the methods on how we can improve the problem of integrating the AI in our medical data, which results proper use of MEDAI in understanding the drugs and patient health chart. This kind of MEDAI report results of capturing the right amount of accuracy in developing the patient health and will be known for its training of the drug detection and recommendation to the doctor, whenever doctor captures their prescription into the model. Although the doctor written notes in the traditional methods are prone to lead into misinterpretation, if anyone assumes it as different drug the chances of the accuracy in maintaining the patient health will be moved from 70% to 93% in recommending the poor adherence of healthcare data.
Keywords: *Medication Errors, Adherence, Natural Language Processing (NLP), MEDAI (Medical AI), Anomaly, Agentic AI.*

1. INTRODUCTION

Obtaining the healthcare information manually and classifying accordingly is quite challenging for the providers or hospitals. Patients' health is the topmost goal for any of caregiver responsibilities. Although the latest trends in the artificial intelligence have taken the place in developing the problems in finding solutions. The human prone errors can be fixed and solved by the proper integration into the model. Over the period in the healthcare the diseases can be predicted upfront knowing the health chart of patients. This way building any kind of model by training for the problem will give immerse results at the end. Proper integration of AI usage in interpreting the realtime data, depending upon the patient health chart and if the medication had any errors to provide any recommendations to the doctor helps a lot in processing the assistance from integration of AI.

The analytical approach in finding the existing models like Agentic AI, which minimalize the human intervention in providing every time problem. The assumptions for any model need to be reduced, because proper trained model with better accuracy in results provide greater methods than having high assumptions. Building a model in finding the pattern for decisions of the problem leads to better solutions in healthcare. The outliner for preventing the patient health by providing the responsible care is a responsibility to undergo in multiple inspections.

Our approach is minimizing the lead of human prone errors which are not intended but with lack of proper knowledge in the case. So, training a model which reads the data of patient in understanding and preprocessing the information of healthcare helps in fostering the better care. The main problem is recognizing the difficult text which are written in hand, these cannot be read by models, since these will not have or follow any pattern of writing. So, feeding the information or following the proper pattern in making the system understand will solve the problem in exhibiting better care for patients.

Leading the way of methods in changing best society for building a path where others to follow in shaping the world. The human prone and poor adherence is very common problem, which no one does knowingly just due to lack of knowledge. Educating with better and best solutions of approaches, building the model like we proposed is a way to solve the problem. The healthcare problems are very sensitive to life matters, so understanding the patient data with preprocessing it as dataset making the MedAI to understand and study helps a lot.

There was a lot of difference in using the best model for solving this use case. The agentic AI and

Generative AI both plays a huge role in enhancing the model, using the correct one to any model differentiates the results on how we need to expect. Agentic AI allows the problem to handle with decision making for the use case and exhibit its full potential for identifying the solution by conditional statements. In our case usage of generative AI is very limited since it works on hallucination of the problem, which will create new data for the provided information. This is quite challenging in finding the best accurate model. The key factors for any AI model are having accurate, relevant and proper least hallucinated one. Medical AI whereas popularly known as MedAI exhibits a greater usage of technology amending in real time provisioned information. The review of all the existing models leaves with a scope of improvement in existing models with the help of latest technologies. Every patient data is crucial and must process with a huge and utmost care. If any misusage or slippery of information leads to greater loss of privacy and transparency. The k most records in finding the better accurate one tunes the model. Supporting the vector indexes for the neighbor nodes will ensure the proper nodes are tagged to the right value. Improper usage of data or human prone errors leads to huge loss of misleading the information of future data prediction.

Daily dosage and proposing the information ensuring it may predict the future, to give better results to the model. Medical data is crucial in understanding to give the right drug dosage for the patient. If any wrong or incorrect dosage is provided to patient leads to serious health care concerns. Long short-term memory of the model ensures it have the previous data in hand to process the information which sequentially understands further to predict the new information. Whereas this is also a great example in understanding further in capturing the predictions based on an analytical data. dynamically interpret patient-specific parameters.

Fakotakis et al. [6] introduced an AI-based acoustic sensing model to evaluate asthma medication adherence using the RDA benchmark. Their research demonstrated that non-traditional input signals like sound could be used to monitor compliance effectively. Inspired by this, our model incorporates the idea of expanding beyond textual analysis. Although the primary goal remains the same usage of OCR to obtain the textual data. And this finetuned further by using NLP processing with the help of Agentic AI's reasoning cycle. It highlighted that adherence detection can extend beyond direct logs into behavioral cues.

Lu et al. [7] implemented a multi-class Support Vector Machine (SVM) approach to model HIV/AIDS treatment adherence, utilizing structured patient data to classify adherence levels. This research influenced the machine learning layer of our anomaly detection module. While our model focuses on unsupervised detection for errors, Lu et al.'s work emphasized that treatment outcomes are heavily influenced by intelligent classification of patient behavior. Their approach highlighted how historical patient data can be used to predict and classify medical compliance, a concept embedded in our Agentic AI's contextual decision-making process.

2. **Related Work**

Recent trends in healthcare domain have been vastly improved in terms modernizations. The electronic health records which are playing huge role in obtaining the proper results H. D. P. dos Santos, A. H. D. P. S. Ulbrich et al [1]. The unsupervised outlier detections for EHR datasets giving no labeled data needed and it's very scalable to use from [1] research study. S. Nousias, A. S. Lalas et al, [2] providing solutions for observing the datasets from the content-based audio classifications which results to provide better results in the respiratory diseases with the high need of accurate model.

L. Tang, X. Zhou et al, [3] care for elderly people is a huge responsibility. It is a great possibility and research on how this communication can be improved among the relatives, doctors, patients and hospitals. This kind of responsible monitoring and providing the proper care to the patients leads to a greater result.

S. R. Minera, A. Nuerbiya et al, [4] the smart way of tracking the usage of pills and making the patients reminders will help the care to do it better. Kropf et al. [5] presented an early-stage implementation of clinical decision support systems (CDSS) integrated into a telemonitoring framework for heart failure patients. Their work emphasized adjusting medication dosages based on established guidelines and physiological feedback. From this study, our model draws the importance of real-time monitoring linked with intelligent rule-based systems. This is laying the foundation for Agentic AI to evolve from static rule-checkers into adaptive, feedback-driven decision makers. Their emphasis on guideline-driven medication adjustments highlighted the need for intelligent systems to Ramesh et al. [8] developed an AI-driven smart pill dispenser using an ESP32 microcontroller, aimed at scheduling and

remotely monitoring medication intake. From this hardware- oriented model, our research was influenced by the adaptive scheduling concept, wherein the Agentic AI assesses risk levels and adjusts its focus or alerting priorities accordingly. Though our model does not involve physical dispensers, the notion of real-time feedback. System adaptability for patient safety directly aligns with our virtual agent's goal- driven behavior. Their work highlighted the role of connected systems in improving patient accountability.
Vimal et al. [9] proposed an intelligent pill dispenser with real-time alerts, remote access, and enhanced safety measures. Their focus on user engagement and alert mechanisms directly inspired the interaction design of our Agentic AI system. Specifically, the idea of triggering alerts only when necessary to reduce fatigue was incorporated into our design. Their work highlighted the need for balanced alert systems that maximize safety without overwhelming patients or clinicians, in our model Agentic AI achieves through contextual analysis and memory-based alert prioritization.

Casciaro et al. [10] proposed a smart pill dispenser aimed at improving medication adherence in elderly populations. Their model focused on usability, simplicity, and integrating visual and auditory alerts to guide medication intake. Although their system was hardware-centric, it highlighted the importance of human-centered design, which influenced the conversational and adaptive interface logic in our Agentic AI. Specifically, their emphasis on minimizing cognitive load for users.

Balaji et al. [11] explored the intersection of Machine Learning (ML) and Internet of Things (IoT) for personalized medication compliance. Their system utilized wearable sensors and ML models to adapt medication reminders to individual patient behaviors. From this work, our model inherits the principle of behavior-driven decision support, allowing Agentic AI to prioritize error alerts based on patient history, adherence trends, and risk profiles. This highlighted the need for personalization in clinical automation, which is core to our adaptive detection pipeline.
K. P. et al. [12] introduced AIRMED—a fully automated, remotely accessible dispenser that evaluates medication schedules and controls delivery. [12] system integrates cloud-based access, user scheduling, and feedback loops, laying the groundwork for remote validation and dynamic scheduling. Our model translates these ideas into software form, where Agentic AI remotely monitors prescription accuracy, evaluates override decisions, and refines detection based on interaction outcomes. This work emphasized the potential of automation combined with clinical evaluation.

Inupakutika et al. [13] provided a framework to measure the responsiveness of cloud- based mHealth applications, highlighting performance metrics such as service response time and data delivery latency. While [13] focus was on cloud performance, it informed the infrastructure design of our model, especially in ensuring that medication error detection remains responsive in real-time clinical environments. The work highlighted the critical role of system latency in decision support efficacy.

Nguyen et al. [14] presented a novel method for pill–prescription matching using Graph Convolutional Networks (GCNs) and contrastive learning. This approach allowed for matching medications with prescriptions even in zero-shot scenarios, where the AI had not encountered the data before. [14] method inspired our Agentic AI to generalize error detection beyond fixed rules and identify unfamiliar patterns in medication instructions. This highlighted the value of representation learning in healthcare models dealing with incomplete or unseen data.

Ganesh and Prakash [15] proposed a deep learning system with triple-sensor integration for detecting physical defects in medicines. Though their focus was on manufacturing, it emphasized the importance of multi-modal sensing and verification. We extended this concept to our domain by cross- verifying prescription accuracy using multiple signals OCR text, historical data patterns, and clinical context. [15] study highlighted the importance of integrity assurance in all stages of medication management, not just dispensing.

3. METHODOLOGY

In understanding the healthcare information and preprocessing them is crucial to adhering to compliance and risk of patients' health. Capturing the patient information and analyzing to give the treatment based on the history is quite challenging if case humans miss the details for any specific cause. Screening the medication errors to fostering the care in adequate manner leads to better results and wellbeing of the patient. The chance in minimizing the hospital costs and providing proper care with less medication errors, have a larger benefit in shaping healthy lifestyle.

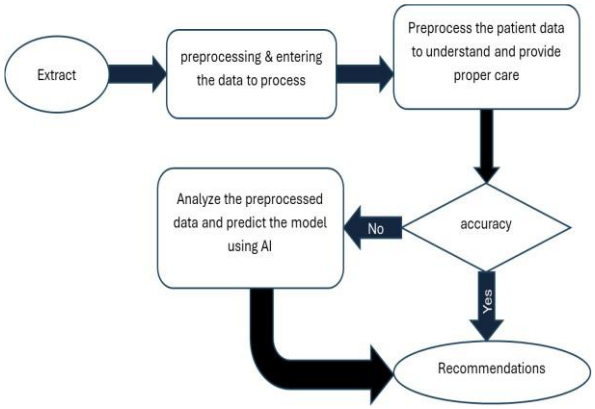

Fig.1 Visual representation of the Flow

Providing the flow and going into the details is very important, at the starting point of any model we need to go through the extraction of the dataset. Fine tuning and providing the significant accuracy for all the top K elements in finding the best suited way to predict the model using Agentic AI.

The modules covering are Existing Methodologies, Tesseract, Materials & Methods and Agentic AI

Section	**Role in Solving the Problem**
Existing Methodologies	Go through with all the existing methods and find the limitations and strengths
Tesseract(OCR Engine)	Extract raw text from handwritten/printed prescriptions or scanned documents

n Errors Using Unsupervised Learning		Define the pipeline and evaluation criteria for error detection		validation
Screening for Medication Errors Using Outlier Detection	Outlier scoring from EHR data patterns		Early detection of anomalous prescriptions	Misses' context-based (clinician intent) errors
Density-Based Outlier Detection for Safeguarding EHR	DBSCAN algorithm on prescription data		Clusters unusual behavior effectively	May misclassify rare but correct actions

Effective Tool for Reporting and Analyzing Errors	Manual reporting NLP on reports	
Automated Misspelling Detection in Clinical Text	Rule-based spelling correction algorithm	
Statistical Anomaly Detection in CDS Systems	Statistical threshold time-series	
CDS Signature Filtering for EHR Audit	Classifier signature modeling	
Misspelling and Abbreviation Correction in Notes	Text mining Levenshtein distance, lexicons	
Understanding & Preventing Wrong-Patient Orders	RCTs of CPOE system changes	
Cranky Comments – Override Reason Analysis	NLP on override logs	
Spelling Correction with First	ML classifier first-rank	
Materials & Methods		
Agentic AI (Autonomous Decision-Maker)	AI	Interpret the extracted data elements if they were prone to errors and automate the decision making

Table 1. Modules purposes

Existing methods	**Method/Technology Used**	**Strengths**	**Limitations / What Could Be Better**
DDC-Outlier: Preventing Medicatio	Unsupervised outlier detection (autoencoders)	No labeled data needed; scalable	High false positive rate; lacks contextual clinical

3.1Existing Methodologies:
xisting limitations
3.2Tesseract:
Using Tesseract, the model built based on the given principles of extracting the raw information which is written in Handwritten slips. This can be avoided by the means of writing the data using system capture. At the end of each patient visits or during the visits if any provider fills up the information directly into the system, the model could predict the best way to recommend and analyze the information that is already available. In this way, the proposing model will predict the best and correct the human prone assumptions.
Each person will have different handwriting which could lead to assumptions and misguiding for the drug dosages. Proper validations and confirmations ensure

Suggestio n Accuracy	prediction	from typos	specific model
Anomaly Detection in Clinical Observati on Data	Semi-supervised encoding, PCA, deep learning	Handles sparse input from clinical streams	Needs extensive tuning; explainabi lity is poor
Medicatio n Safety Analysis with Smart Dashboar ds	Visual analytics, event mining from logs	Helps pharmacis ts catch dose/timin g errors	Visual bias; dependent on completen ess of logs

anything can be achieved using the better preprocessing technique.

3.3MATERIALS AND METHODS:
The process of extracting the right value into the finding right and human error prone model is to have the best pipeline. To understand this proposing to
create a pipeline, which takes the OCR optical character recognition. This follows by the preprocessing the right number of datasets, this could be in any form of datasets such as text, handwritten notes and any kind of scanned documents. These kind of form of texts helps in improving the model in better identification and processing the correct train datasets.
The feature and data correcting can be done using the NLP correction, which allows the processed datasets is well written or not. The correction can be included such as spell check, grammar, or any kind of potential issues related to text. This way of eliminating the noises from the dataset, ensure the model predicts the data correctly.
Detecting the anomaly in the prescribed information leads a crucial role. Labelling them upfront by knowing if it is correctly, wrong labelling. This way rule-based anomalies can be identified and predicted to act if they were any suspicious or unusual prescriptions. Anomalies enable the feature entanglement in adapting them in medical data. Finding the patterns in datasets which were processed through the part

of speech tagging, tokenization and text extraction, from them the anomalies identify in elimination.

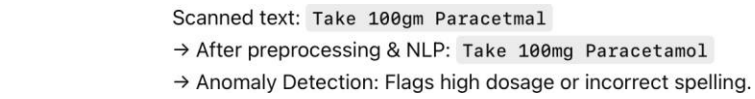

Fig.1. Before and after preprocessing

Flagging them based on the scanned text as Fig.1, gives the proper results in finding the right prescription. To validate the best methods in practice, we need to analyze all the existing metrics to process all possible solutions in identifying the metrics. The main key elements that include in process of medication errors identifications were accuracy, f1 score and precision. If these elements are processed and captured correctly the matrix of the datasets will be obtained correctly.

3.3.1. DataSource:

Finding the electronical health records (EHR), enables the right number of datasets have been fetched and preprocessed correctly in extracting and trained them correctly, because these datasets provide the past patient information and drug usages. Scanned prescriptions, getting the extracted texts and processing them to the feed of our model will find the anomalies. Using of the tesseract the subgroup of OCR optical character recognition, enables the greater scope for converting the unstructured datasets. The pharmacy logs which were tracked and cross checked against whether they were labelled and tagged as prescribed, dispensed or administered.

3.3.2. Techniques used:

Fixing any kind of common spelling and grammar corrections helps in identifying the problems right away as the first crucial step. This could potentially eliminate the noises in the datasets. The new methods of OCR in usage of tesseract captures the dataset algorithmically and extracts the information from it. Usage of the noise elimination by identifying based on the Natural language processing of text to speech conversion in identifying and fetching the anomalies in understanding of the data.

Levenshtein Distance this helps in finding the distance between strings to identify and correct the drug name typos. It forms the correct name if needed by insertion, deletion and updating of the existing string. This ensures to form the right string even though it has the typos. It ensures to find and observe the similarities across each way it is possible even if it has the medical data errors.

3.3.3. Named Entity Recognition (NER):

This makes the model further enhancement, since it has the capability to sub entity of each portion to an entity. For example; if we have the paracetamol 100gm, it is further classified to take paracetamol 100mg because it contains some anomaly, flag of high dosage or incorrect spelling. This further ensures to capture them as entities by classifying them as drug name, dosage, units and frequency etc., because of these classifications the model will be enhanced better way where it will be the go to place which consists of right amount of dosage for the patient depending upon their history of past dataset.

3.4Agentic AI:

The integration of Agentic AI into the healthcare systems gives a greater decision support to automate the decision making and be context aware of the intelligence. This is capable of greater possibilites in interpreting the complexity of various scenarios in healthcare. Although the pharmacy detections using agentic AI gives a wide range of methods by eliminating the traditional ways of rules and engines by simplifying the anomaly detections.

Unlike of static methods which rely on the predetermined thresholds or rigid workflows, these methods capture the agentic AI functions with a proper sense of purpose, holding of memories and adaptabilities. These methods act as not only as tool, but also a digital guiding tool which learns from reasons and long-term memory of the past datasets. For example, if we are analyzing the prescription using OCR technique like tesseract tool, the Agentic AI matches the dosage, drug names and all other parameters by itself, in understanding the main use case.

Instead, it enables the understanding of patient information and monitors the prescription from past decisions. There will be inconsistences which might be significant improvement of clinical data. If any dosage appears to be high then the AI doesn't just flag it, it also assesses whether a similar dose was previously used for the same kind of patient or not, considering the factors like weight, height, symptoms and other potential factors.

Moreover, Agentic AI can simulate a clinical feedback loop. If an anomaly is detected, it generates an explainable alert and records the clinician's response to improve future decision-making.

For example, if a physician overrides a flagged dose with a valid explanation, the model tunes its internal

model to avoid unnecessary alerts in similar contexts. This self-refining behavior minimizes alert fatigue, a major barrier in current clinical decision support systems. The proper usage of Agentic AI can autonomously review dispensing logs, cross-check with electronic health records, and detect patterns like duplicate prescriptions.

In essence, it prioritizes critical cases and generate contextual suggestions allows it to function as a virtual medication safety officer embedded within the digital infrastructure.

What sets it apart is its ability to retain context, set goals, and initiate action not just react to inputs. In error detection this translates into a system that not only finds problems but actively contributes to preventing them by learning from every decision it processes.

The final transformation of medication safety from a reactive check into a proactive process, offering healthcare providers a reliable partner in reducing harm and improving outcomes.

4. Comparision of usage:

Model Setup	**Outcome Measured**
Without Tesseract (Manual Entry Only)	May miss handwritten errors, or manual entries may be incorrect/incomplete. Lower recall.
Without Agentic AI (Traditional Rule- Based Only)	No adaptability
With Tesseract + Agentic AI	End-to-end automation: reads scanned docs, understands context, makes intelligent decisions. Likely higher precision, better real-world usability.

Table.3. Comparision chart if proposed methods not used explaining the potential risks.

The results suggest that this hybrid system can enhance medication safety by not only detecting probable errors but also minimizing false alerts and improving overall efficiency. This supports a safer prescribing and dispensing environment and opens pathways for intelligent automation in clinical workflows.

Enabling long-term memory and reinforcement learning within the agent can help the model continuously adapt. This will adapt to individual clinician styles, local prescription trends, and evolving treatment guidelines.

Proposed model is using most of the adaptable techniques in providing the best solutions. If the tesseract is not available, then the manual entry is highly prone to human errors. This leads to incomplete and miss handwritten errors or manual entries. Due to this the precision and recall of the dataset will be hugely reduced.

The traditional methods of usage of AI will improve the coding practices and it creates more adaptability, and alternatives will be generated in over the period. The training dataset will be huge, so that the data will not be act as old or not used ones. The coding complexity will be increased rapidly, due to this matter of fact. The responsible usage of AI will be huge profitable in terms of adaptability in nature and, the techniques can be hugely varied across.

Using the Cross-Institutional Data Sharing establishes the federated learning approach between hospitals or pharmacies. This contributes anonymized data to improve the error detection system while preserving patient privacy.

Proper Patient-Centered Applications Integration can simplify the version into the mobile apps for patients. This allows the patients to track their self-risk in maintaining and the model adaptability.

The Clinical Trial and Regulatory Adoption involves testing the system in live clinical environments. This could create ethical oversight to validate its impact on real-world safety outcomes and its alignment

with healthcare regulations.
The above techniques can be shown more growth in the problem of adapting the agentic ai in the real-world problems. The proposed pipeline reduces the gaps between the provider and patients, to foster the better healthcare system, with less prone of errors.

5. CONCLUSION AND FUTURE SCOPE

Our research finds the best methods in capturing the human prone errors with the usage of OCR model as Tesseract, and NLP techniques. These enabled to remove the noises and propose the best technique in finding the right accurate output. Since the traditional and handwritten texts from the providers are error prone and poor adherence to follow, the usage of agentic ai and anomaly removal reduces the errors down to 93%. This results in best proposed solution. All the captured results and studies from the different sources, have provided more insights on the areas of improvement. Agentic AI usage makes the model to understand and read from the dataset which is already present from the clinical expertise. This way it first analyzes and provides the autonomous results in

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