# Applying Artificial Intelligence to create risk stratification visualization for underserved patients to improve population health in a community health setting

**Don Roosan** ( droosan@westernu.edu )
Western University of Health Sciences

**Moom R Roosan**
Chapman University

**Soyoung Kim**
Western University of Health Sciences

**Anandi V Law**
Western University of Health Sciences

**Christ Sanine**
EMANATE HEALTH

**Research Article**

**Keywords:** Artificial Intelligence, Cognitive task analysis, Electronic Health Record, data Visualization

**Posted Date:** May 20th, 2022

**DOI:** https://doi.org/10.21203/rs.3.rs-1650806/v1

# Abstract

Current healthcare visualizations utilize unstructured Electronic Health Record (EHR) data that lack user requirement analysis for intuitive visualizations. Since clinicians are the end-users, it is crucial to consider end users' input to improve clinical workflow efficiency. In this paper, we developed a user-centered design through cognitive task analysis (CTA) to visualize unstructured EHR data using artificial intelligence (AI) and natural language processing (NLP). The research team conducted CTA with 8 clinicians. The interviews were transcribed, and a content analysis was performed. Themes were coded, and user requirements helped us to understand the clinical workflow. The CTA resulted in 5 different themes: 1) Gathering patient information, 2) Filtering and searching for necessary information, 3) Subjective, objective assessment, plan of the patient, 4) Visualization of unstructured EHR data, and 5) Progression of trends and comparisons in patients. The intuitive visualization dashboard utilizing unstructured EHR population data was successfully developed. Design elements included an interactive dashboard with a snapshot and basic information for all patients, filter and search keywords, and visualizations of patient trends and lab results through graphs. Finally, a system usability scale (SUS) survey was completed to assess the usability of the dashboard by 20 participants. The completed 20 SUS surveys resulted in an average score of 80.9, which concluded that the platform had a high usability. The health analytics dashboard demonstrated unstructured data containing diverse information that can support identifying underserved populations, enhance workflow efficiency and create intuitive design interface.


# Introduction

Big data pertains to large volumes of diverse datasets that cannot be analyzed, managed, or contained by traditional methods in industries such as business, marketing, or social media [1, 2]. In the healthcare sector, big data exists in various forms such as mobile health applications, medical monitoring devices and electronic health records (EHRs). Much of real-world evidence research utilizes structured EHR data for comparative effectiveness studies, retrospective analysis, and predicting disease progression [3–6]. Structured EHR data refers to datasets that are standardized and can be easily retrieved to store lab values, ICD codes, or patient demographics. Unstructured data, on the other hand, refers to datasets that are not as easily retrievable and exist mainly as free texts such as physician, nurse, or pharmacy progress notes, MRIs, EKGs, etc [7]. More than 80% of healthcare data is unstructured which holds diverse crucial patient data with numerous potential applications [1]. Unfortunately, unstructured data remains underutilized because it is not as easily accessible for information processing. Therefore, it is imperative to create functionalities to process the data to understand the clinical complexity in healthcare [8–12]. In addition, unstructured data provided a more in-depth picture of the classification of clinical problems when compared to using only claim data or structured data [13]. Unstructured data offers a complete and more detailed picture of diagnosis, disease progression, and disease burden than structured data alone.

One way to explore unstructured data is to combine artificial intelligence (AI) with natural language processing (NLP) methods to text mine clinical progress notes. NLP is an area of computer science that consists of studying, identifying, and retrieving the human language into its natural form to extract

information [14]. NLP can be used to verify and extract information from unstructured datasets. Multiple studies have included NLP with AI methods to successfully analyze unstructured data [12, 15–18]. Although previous studies illustrate the feasibility of creating a platform or machine learning algorithm for mining unstructured data, the considerations for user requirement analysis are often overlooked [16, 19–22]. Studies that demonstrate the ability to text mine unstructured data are important to researchers but may not be as easily usable or applicable for the clinicians [23–25]. Both structured and unstructured data is critical for accomplishing clinical duties. Hence, the development of EHR data design must consider intelligent visual analytics [26]. Visualizations in healthcare help clinicians to query for select information in a timely manner, improve decision making, and understand patterns [27].

In order to create an intuitive interface for the clinicians, a user requirement analysis is necessary. User requirement analysis is a technique based on human factor-based methods [28–32]. In the time of COVID-19, it is clear that data sharing is crucial to obtain patients' health records such as immunization records and medication lists [33, 34].

Significant opportunities exist for operationalizing unstructured data. A predictive model for hospital readmissions and early diagnosis of disease states such as heart failure has been developed using unstructured data [15, 35–37]. Furthermore, unstructured data has the potential to improve quality measures and population health management [19]. However, there is a critical need in understanding how to develop an intuitive interface for population health data analytics dashboards. Although many studies have researched using AI and NLP methods to create health analytics dashboards, very few considered the user's perspectives. Visualizing unstructured data utilizing AI and NLP methods have not been studied in depth [27]. In this paper, unstructured EHR data was used to create an interactive analytics dashboard to assist healthcare providers in understanding the patient's overall clinical situation. The objective of this research was to develop a user-centered design with an AI and NLP-based approach to visualize unstructured datasets while complementing clinicians' higher cognitive skills.

## Methods

The study took place at Emanate Health and was approved by the Institutional Review Board at Western University of Health Sciences. There were three steps to create the dashboard. The first step began with understanding user requirements using cognitive task analysis (CTA). In the second step, the results from user requirements were utilized to design the AI-based analytics dashboard for visualizing unstructured data. Finally, a System Usability Scale (SUS) survey was given to assess the functionalities of the data analytics dashboard. Figure 1 illustrates the methods from Steps 1–3.

# 1) Cognitive Task Analysis

In this research, we used CTA to identify user requirements to develop an efficient visualization dashboard to organize patient data. Interviews took place with 8 stakeholders including 5 nurses, and 3 pharmacists. Specific user requirements were addressed through the interviews. A qualitative thematic

analysis was conducted iteratively by three independent reviewers with healthcare backgrounds. The content analysis was accomplished by initially reviewing the entire transcriptions, coding the data, and creating an overall theme to encompass the various codes [38]. The analysis was finalized through multiple sessions to refine the selected themes. The themes were verified, and discrepancies were discussed among the research team until a consensus was reached.

# 2) Health Analytics Dashboard

We collected data from EHR on 500 inactive patients and removed all HIPAA identifiers. The dataset was curated in an excel file and cleaned for using NLP and AI algorithms. The process of this step is described in Fig. 2.

In this study, we used MetaMap, an NLP tool to extract biomedical concepts from a free-front text developed by the National Library of Medicine (NLM) [39]. Our research team took input text into words or phrases through a lexical/syntactic analysis including sentence boundary determination, parts of speech tagging, parsing and generating variants of the phrase words. Using the United Medical Language System (UMLS), MetaMap then identifies all possible candidate terms to evaluate the matched phrases retrieved in the previous process based on measures of centrality, variation, cohesiveness and coverage. After categorizing, a concept unique identified (CUI) with a score between 0 to 1000 on the strength of mapping is generated [40]. A series of text preprocessing identifies the CUIs from the EHR's dataset. We used Google's spell checker API to correct any misspelled words. We created a list with the scoring system to apply the ML algorithm to the dataset.

Recursive neural network (RNN) is a type of artificial neural network with feedback features to store memory and feedforward to learn and anticipate the next output [41]. We used a previously validated context-specific recursive neural network (CRNN) proven with high sensitivity and specificity of texts. These networks can induce distributed feature presentations for never seen words and texts. Moreover, the CRNN model accurately predicts phrase structure trees with syntactic information [42]. Using this model, our backend data server created a pivot table of sparse texts with scoring and created a loop learning method. Finally, we used a Python script to pull the texts and associated lab values to create the analytics visualization dashboard. This visualization can utilize the CRNN model to predict a specific patient's trend as well as show the past trend. For example, if a patient has a blood glucose level for the last 3 days, based on the ML model, our system can predict blood glucose level in the next 3 days with more than 80% accuracy while using other clinical data. Finalized data analytics dashboard using unstructured data from a separate deidentified source was presented to clinicians for feedback. The research team incorporated all feedback in the design until no further issues were identified.

# 3) System Usability Scale (SUS) survey

Twenty participants were chosen to complete a System Usability Scale (SUS) survey. SUS is a 10-item questionnaire that studies the user experience and reviews the platform for design iterations. The survey contained a 5-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree. The raw data was multiplied by 2.5 to get the final score between 0 and 100 [43].

## Results

# 1) Cognitive Task Analysis

The coded themes and examples are outlined in Table 1. Responses to questions were similar across all stakeholders. Five overarching themes were identified including 1) gathering patient information, 2) filtering and searching for necessary information, 3) subjective, objective, assessment, and plan, 4) visualization of unstructured EHR data, and 5) trends of patient progression and comparisons in graphs.

Table 1
Coded themes from stakeholder responses to interview questions.

| Coded theme | Example |
|---|---|
| Gathering patient information | "…review current inpatient patients (admits), see if there was any discharge overnight, if so change to outpatient status. Schedule to call discharged patients…" |
| Filter and search for necessary information | "…Filtering/screening 'reasons for dx' or 'reasons for admit' would be helpful, especially if could look into PHM, would save time when screening..." |
| Subjective, objective, assessment, plan of patient | "…look at signs and symptoms, lab values that support the target diagnosis (ex: would look CXR, BNP, EF for CHF). Also look at plan/assessment from doctor, and diagnosis data/info verbiage for COPD CHF, pneumonia." |
| Visualization of unstructured EHR data | "The presentation varies, but for daily workflow it would ideally be in a list with patient names, medical record number, location (unit), insurance, etc.." |
| Patient progress trends and comparisons in graphs (i.e. bar, pie) | "Trends and progression graphs" |

For current workflow, all interviewees are required to know patient diagnosis and demographics, insurance status, and side effects of medications. However, it is difficult to find the necessary information from the current EHR due to disjointed information. Instead of manually searching for each piece of information, the workflow allowed a single place to verify, view, and determine patient information.

To make the workflow easier, stakeholders mentioned requiring the ability to quickly vet information through pulling and filtering free text information. Manually reading through every single progress and chart note was time-consuming. Thus, the code for an easier workflow selected was to filter and search for necessary information. Stakeholders mentioned this would save them time and be able to stratify patients, which result in improving their workload.

Some specific information that was required for patient care was subjective, objective, assessment and plan (SOAP). Stakeholders are required to see all aspects of the health of the patient: labs, medications, past medical history, consultations, surgeries, etc. The resulting theme was the SOAP format information.

Patient information and treatment plan were necessary to understand each case and make decisions for essential care.

For the visualization questions, stakeholders desired a platform where they could easily see unstructured patient data and also the progress of the patient's trends. Stakeholders mentioned the current way of displaying patient information was through multiple pages. Instead, they suggested visualizing all patient information in one place with multiple patients as a table format, charts, or graphs.

Finally, intuitive visualizations could aid in stakeholders' day to day work environment to be effective which allows them to review trends, compare data, and patient progress at a glance. Stakeholders mentioned having a one snapshot view in the visualization dashboard area would be highly beneficial.

# 2) Health Analytics Dashboard

The developed dashboard included three main functionalities. First, the machine learning algorithm processed unstructured EHR data and parsed it into meaningful information. The visualized information can support clinicians to understand a patient's severity and acuity in one snapshot. Second, the visualization snapshots of patient progress use clear graphics and visual tools to instantly comprehend the patient lab trends and testing results. The AI algorithm can also show a list of patients based on their race or ethnicity. Third, the data from the platform can be downloaded into any file format such as a Microsoft Excel sheet or CSV file.

Figure 3 represents snapshots of the platform. Figure 3a and 3b were created in response to multiple comments regarding visualizing trends and patient's vitals and lab values in one place instead of checking multiple areas of the EHR to find data. Figure 3a represents vitals such as temperature and blood pressure and Fig. 3b represents lab values such as glucose and hemoglobin. Clinicians and nurses are able to view the trends and make appropriate interventions. For each patient, the trends were depicted as scattered plots connected with lines. Figure 3c represents the solution to that request. In the search bar, clinicians are able to type in certain measures such as blood pressure > 120 to identify patients who have elevated blood pressure requiring intervention. Figure 3c illustrates the search result that found 4 patients who matched and had systolic blood pressure > 120. This could be done with other clinical markers such as lab values, diagnosis, or medications. Figure 3d represents an instance when the clinician searches for patients who take warfarin. The search resulted in categorizing patients who are currently on warfarin and patients who have active problems from taking warfarin. The results are represented in a pie chart with ratios of patients with warfarin and other medications from insulin to atorvastatin. Clinicians were able to view drug-drug interactions and adverse drug events through this resulting page. Some problems with patients on warfarin consist of hypertension, anemia, and active bleeding. Users can also search other medications as well in order to see the impact on the patient population. The visualization utilized the CRNN model to predict a specific patient's trend and the past trend. For example, if a patient has a blood glucose level of 160 for the last 3 days, based on the ML model, our system can predict blood glucose level in the next 3 days with more than 80% accuracy.

## 3) SUS Survey

For the SUS survey, participants included clinicians, pharmacy coordinators, nurses, hospital administrators and social case workers. Of the 20 participants, 14 were female and 6 were male. All 20 participants completed the SUS survey. The average raw score was 32.35 and the average final score was 80.9 with a standard deviation of 5.69. The individual scores are graphed as shown in Fig. 4.

# Discussion

Previous studies developed analytics dashboards from population data for research in various settings. One particular study used data from EHRs to better study cancer registries [20]. Other studies mined data for pharmacovigilance, phenotyping genetic diseases, and mobile health technology [44]. However, very few studies are considered user-friendly interface designs while developing the systems. This paper contributes to population-level unstructured data literature by creating an AI with NLP based approach to managing unstructured datasets with the integration of results from the CTA. We were able to successfully incorporate CTA results into our web-based HIPAA-protected platform to efficiently represent unstructured patient data. Furthermore, stakeholders desired an easy visualization of patient status, progress, and plan. One of the elements that were included was a text search for users to search for exact items that they needed to find a specific patient. For example, multiple stakeholders commented that the first thing they do once they begin their shift is look through which patients need to be followed up per protocol. Another aspect of the design was the inclusion of pie charts and line graphs to determine patient progress and identify problem areas. Finally, the ability to search for medications would be a more effective way for clinicians to monitor patients and select patients who need to be closely observed. For instance, the warfarin search would be useful not only to determine the number of patients affected by warfarin but also to provide monitoring parameters for these patients with active problems. One of the main issues stakeholders were concerned about the current EHRs was that it was not easy to find patient information all in one place. They had to sift through multiple pages in different areas to find each piece of information. Current EHR designs hold lab values in the results section, but the results of EKGs and MRIs might be stored either in the notes or images section. Our web-based platform addressed stakeholders' concerns efficiently. The SUS score totaled to 80.9 from 20 participants, which is interpreted as a high score when compared to the average of 68. The score of 80.9 would be in the top 10 percentile describing a high usability.

Data that are visually analyzed and presented can not only impact providers but also patients and population health. Using our innovative visualization of unstructured data, clinicians have the ability to monitor patients more effectively and efficiently. One such visualization dashboard, Lifeline2 allowed providers to view data based on specific time sections and search for details that helped improve patient care through collaborating with end-users [37]. A different study developed an EHR informational display tool with distinct design features that allowed clinicians to view data quicker [45]. Both of the studies have implications for improving designs and visualizations that can impact provider clinical judgment by

supporting the higher cognitive skills of clinicians. Therefore, the analytics dashboard we developed and described has the necessary visualizations to assist clinicians in their patient care activities.

The developed dashboard was strategically selected to be web-based due to the accessibility of health information exchange (HIE). HIE is the ability to exchange patient information in a secure manner to promote efficient patient care and interoperability. The contemporary fragmented healthcare system in the United States and different EHR companies result in the inability to exchange information. Health data standards are a crucial element for data sharing which range from genomics to clinical data [46]. As a result, health information is not easily obtainable or transferrable through technology. Interoperability would not only improve patient care, and continuity of care, and reduce the administrative burden on practitioners, but it would also provide a more precise picture for real-world research. Standards exist for EHR messaging including HL7 Clinical Document Architecture (CDA) and HL7 Fast Healthcare Interoperability Resources (FHIR) [31,32,47. 48, 49,50]. However, established standards have yet to provide an all-inclusive method for every type of data in EHRs [51]. Although the study concludes that more work is required for a fully capable interoperable system, it provides insight into a feasible method. Thus, our developed dashboard data is interoperable and shareable across multiple EHR vendors.

# Limitations

There were two main limitations to our data analytics dashboard. The first limitation is that the backend data from the dashboard did not automatically transfer data from the EHR. Unstructured data was pulled separately and integrated to the dashboard. The second limitation is the lack of analytical features since it was not directly connected to the EHR. For example, physicians would not be able to open up the EHR to view patients' records through the dashboard.

## Conclusion

We successfully developed web-based dashboard analytics from unstructured data to provide visualizations to support clinician workflow through AI and NLP methods. The visualizations for the dashboard were designed based on a CTA. The results from CTA were used to create the design of the interface including word searches for patients on certain medications or specific clinical markers, graphical representations of patient progress, and a single page for patient status. A SUS survey was completed by 20 participants with a resulting score of 80.9 concluding high usability. The AI-based dashboard demonstrated an intuitive interface displaying unstructured data to support our clinicians in improving patient care.

## Declarations

### Funding

The work has been supported by a grant from Emanate Health and Western University of Health sciences.

### Competing Interests

The authors have no competing interests to declare that are relevant to the content of this article.

### Ethics Approval

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards. The study was approved by the Institutional Review Board of the Western University of Health Sciences.

### Author Contributions

All authors contributed to the study's conception and design. Material preparation, data collection and analysis were performed by Don Roosan, Chris Sanine, and Moom Roosan. The first draft of the manuscript was written by Don Roosan and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

### Consent to participate

Verbal informed consent was obtained prior to the interview.

## References


1. Kong HJ. Managing Unstructured Big Data in Healthcare System. *Health Inform Res*. 2019;25(1):1-2. doi:10.4258/hir.2019.25.1.1
2. Collins FS, Morgan M, Patrinos A. The Human Genome Project: Lessons from Large-Scale Biology. *Science*. 2003;300(5617):286-290. doi:10.1126/science.1084564
3. Wu LT, Gersing K, Burchett B, Woody GE, Blazer DG. Substance use disorders and comorbid Axis I and II psychiatric disorders among young psychiatric patients: findings from a large electronic health records database. *J Psychiatr Res*. 2011;45(11):1453-1462. doi:10.1016/j.jpsychires.2011.06.012
4. Fiks AG, Grundmeier RW, Margolis B, et al. Comparative Effectiveness Research Using the Electronic Medical Record: An Emerging Area of Investigation in Pediatric Primary Care. *J Pediatr*. 2012;160(5):719-724. doi:10.1016/j.jpeds.2012.01.039
5. Klompas M, Eggleston E, McVetta J, Lazarus R, Li L, Platt R. Automated Detection and Classification of Type 1 Versus Type 2 Diabetes Using Electronic Health Record Data. *Diabetes Care*. 2013;36(4):914-921. doi:10.2337/dc12-0964
6. Desautels T, Calvert J, Hoffman J, et al. Prediction of Sepsis in the Intensive Care Unit With Minimal Electronic Health Record Data: A Machine Learning Approach. *JMIR Med Inform*. 2016;4(3):e5909. doi:10.2196/medinform.5909

7. Raghupathi W, Raghupathi V. Big data analytics in healthcare: promise and potential. *Health Inf Sci Syst*. 2014;2:3. doi:10.1186/2047-2501-2-3
8. Islam R, Weir C, Del Fiol G. Heuristics in Managing Complex Clinical Decision Tasks in Experts' Decision Making. *IEEE Int Conf Healthc Inform IEEE Int Conf Healthc Inform*. 2014;2014:186-193. doi:10.1109/ICHI.2014.32
9. Islam R, Weir CR, Jones M, Del Fiol G, Samore MH. Understanding complex clinical reasoning in infectious diseases for improving clinical decision support design. *BMC Med Inform Decis Mak*. 2015;15:101. doi:10.1186/s12911-015-0221-z
10. Islam R, Weir C, Fiol GD. Clinical complexity in medicine: A measurement model of task and patient complexity. *Methods Inf Med*. 2016;55(1):14-22. doi:10.3414/ME15-01-0031
11. Islam R, Mayer J, Clutter J. Supporting novice clinicians cognitive strategies: System design perspective. *IEEE-EMBS Int Conf Biomed Health Inform IEEE-EMBS Int Conf Biomed Health Inform*. 2016;2016:509-512. doi:10.1109/BHI.2016.7455946
12. Hernandez-Boussard T, Monda KL, Crespo BC, Riskin D. Real world evidence in cardiovascular medicine: ensuring data validity in electronic health record-based studies. *J Am Med Inform Assoc JAMIA*. 2019;26(11):1189-1194. doi:10.1093/jamia/ocz119
13. Kharrazi H, Anzaldi LJ, Hernandez L, Davison A, Boyd CM, Leff B, et al. The Value of Unstructured Electronic Health Record Data in Geriatric Syndrome Case Identification. Journal of the American Geriatrics Society. 2018;66(8):1499-507.
14. Chowdhury GG. Natural language processing. *Annual Review of Information Science and Technology (ARIST)*. 2003 Jan 1;37:51-89.
15. Jagannatha AN, Yu H. Bidirectional RNN for Medical Event Detection in Electronic Health Records. *Proc Conf Assoc Comput Linguist North Am Chapter Meet*. 2016;2016:473-482.
16. Hong N, Wen A, Shen F, et al. Integrating Structured and Unstructured EHR Data Using an FHIR-based Type System: A Case Study with Medication Data. *AMIA Summits Transl Sci Proc*. 2018;2018:74-83.
17. Chu J, Dong W, He K, Duan H, Huang Z. Using neural attention networks to detect adverse medical events from electronic health records. *J Biomed Inform*. 2018;87:118-130. doi:10.1016/j.jbi.2018.10.002
18. Sung SF, Chen K, Wu DP, Hung LC, Su YH, Hu YH. Applying natural language processing techniques to develop a task-specific EMR interface for timely stroke thrombolysis: A feasibility study. *Int J Med Inf*. 2018;112:149-157. doi:10.1016/j.ijmedinf.2018.02.005
19. Kruse CS, Goswamy R, Raval Y, Marawi S. Challenges and Opportunities of Big Data in Health Care: A Systematic Review. *JMIR Med Inform*. 2016;4(4):e38. doi:10.2196/medinform.5359
20. Cha HS, Jung JM, Shin SY, et al. The Korea Cancer Big Data Platform (K-CBP) for Cancer Research. *Int J Environ Res Public Health*. 2019;16(13):2290. doi:10.3390/ijerph16132290
21. Ng K, Ghoting A, Steinhubl SR, Stewart WF, Malin B, Sun J. PARAMO: A Parallel Predictive Modeling Platform for Healthcare Analytic Research using Electronic Health Records. *J Biomed Inform*. 2014;48:160-170. doi:10.1016/j.jbi.2013.12.012

22. Sammani A, Jansen M, Linschoten M, et al. UNRAVEL: big data analytics research data platform to improve care of patients with cardiomyopathies using routine electronic health records and standardised biobanking. *Neth Heart J*. 2019;27(9):426-434. doi:10.1007/s12471-019-1288-4
23. Roosan D, Weir C, Samore M, et al. Identifying Complexity in Infectious Diseases Inpatient Settings: An Observation Study. *J Biomed Inform*. 2017;71 Suppl:S13-S21. doi:10.1016/j.jbi.2016.10.018
24. Roosan D, Samore M, Jones M, Livnat Y, Clutter J. Big-Data Based Decision-Support Systems to Improve Clinicians' Cognition. *IEEE Int Conf Healthc Inform IEEE Int Conf Healthc Inform*. 2016;2016:285-288. doi:10.1109/ICHI.2016.39
25. Roosan D, Karim M, Chok J, Roosan M. Operationalizing Healthcare Big Data in the Electronic Health Records using a Heatmap Visualization Technique. In: ; 2022:361-368. Accessed May 11, 2022. https://www.scitepress.org/Link.aspx?doi=10.5220/0008912503610368
26. Keim DA, Mansmann F, Schneidewind J, Thomas J, Ziegler H. Visual Analytics: Scope and Challenges. In: Simoff SJ, Böhlen MH, Mazeika A, eds. *Visual Data Mining: Theory, Techniques and Tools for Visual Analytics*. Lecture Notes in Computer Science. Springer; 2008:76-90. doi:10.1007/978-3-540-71080-6_6
27. Shneiderman B, Plaisant C, Hesse BW. Improving Healthcare with Interactive Visualization. *Computer*. 2013;46(5):58-66. doi:10.1109/MC.2013.38
28. WHITEFIELD A, Wilson F, Dowell J. A framework for human factors evaluation. *Behav Inf Technol - Behav IT*. 1991;10:65-79. doi:10.1080/01449299108924272
29. Roosan D, Law AV, Karim M, Roosan M. Improving Team-Based Decision Making Using Data Analytics and Informatics: Protocol for a Collaborative Decision Support Design. *JMIR Res Protoc*. 2019;8(11):e16047. doi:10.2196/16047
30. Roosan D, Li Y, Law A, et al. Improving Medication Information Presentation Through Interactive Visualization in Mobile Apps: Human Factors Design. *JMIR MHealth UHealth*. 2019;7(11):e15940. doi:10.2196/15940
31. Roosan D, Chok J, Karim M, et al. Artificial Intelligence–Powered Smartphone App to Facilitate Medication Adherence: Protocol for a Human Factors Design Study. *JMIR Res Protoc*. 2020;9(11):e21659. doi:10.2196/21659
32. Karwowski W. Ergonomics and human factors: the paradigms for science, engineering, design, technology and management of human-compatible systems. *Ergonomics*. 2005;48(5):436-463. doi:10.1080/00140130400029167
33. Li Y, Duche A, Sayer MR, et al. SARS-CoV-2 early infection signature identified potential key infection mechanisms and drug targets. *BMC Genomics*. 2021;22:125. doi:10.1186/s12864-021-07433-4
34. Sayer M, Duche A, Nguyen TJT, et al. Clinical Implications of Combinatorial Pharmacogenomic Tests Based on Cytochrome P450 Variant Selection. *Front Genet*. 2021;12:719671. doi:10.3389/fgene.2021.719671
35. Wang Y, Ng K, Byrd RJ, et al. Early Detection of Heart Failure with Varying Prediction Windows by Structured and Unstructured Data in Electronic Health Records. *Conf Proc Annu Int Conf IEEE Eng*

*Med Biol Soc IEEE Eng Med Biol Soc Annu Conf*. 2015;2015:2530-2533. doi:10.1109/EMBC.2015.7318907

36. Shadmi E, Flaks-Manov N, Hoshen M, Goldman O, Bitterman H, Balicer RD. Predicting 30-Day Readmissions With Preadmission Electronic Health Record Data. *Med Care*. 2015;53(3):283-289.
37. Vest JR, Grannis SJ, Haut DP, Halverson PK, Menachemi N. Using structured and unstructured data to identify patients' need for services that address the social determinants of health. *Int J Med Inf*. 2017;107:101-106. doi:10.1016/j.ijmedinf.2017.09.008
38. Islam R, Weir CR, Jones M, Del Fiol G, Samore MH. Understanding complex clinical reasoning in infectious diseases for improving clinical decision support design. *BMC Med Inform Decis Mak*. 2015;15:101. doi:10.1186/s12911-015-0221-z
39. Aronson AR. MetaMap: Mapping Text to the UMLS Metathesaurus. :26.
40. Aronson AR, Lang FM. An overview of MetaMap: historical perspective and recent advances. *J Am Med Inform Assoc JAMIA*. 2010;17(3):229-236. doi:10.1136/jamia.2009.002733
41. Fine TL. Fundamentals of Artificial Neural Networks [Book Reviews]. *IEEE Trans Inf Theory*. 1996;42(4):1322. doi:10.1109/TIT.1996.508868
42. Socher R, Manning CD, Ng AY. Learning Continuous Phrase Representations and Syntactic Parsing with Recursive Neural Networks. :9.
43. Mclellan S, Muddimer A, Peres S. The Effect of Experience on System Usability Scale Ratings. *J Usability Stud*. 2011;7.
44. Ross MK, Wei W, Ohno-Machado L. "Big Data" and the Electronic Health Record. *Yearb Med Inform*. 2014;9(1):97-104. doi:10.15265/IY-2014-0003
45. O'HARE D, WIGGINS M, WILLIAMS A, WONG W. Cognitive task analyses for decision centred design and training. *Ergonomics*. 1998;41(11):1698-1718. doi:10.1080/001401398186144
46. Roosan D, Hwang A, Law AV, Chok J, Roosan MR. The inclusion of health data standards in the implementation of pharmacogenomics systems: a scoping review. *Pharmacogenomics*. 2020;21(16):1191-1202. doi:10.2217/pgs-2020-0066
47. Kim E, Baskys A, Law AV, Roosan MR, Li Y, Roosan D. Scoping review: the empowerment of Alzheimer's Disease caregivers with mHealth applications. *NPJ Digit Med*. 2021;4:131. doi:10.1038/s41746-021-00506-4
48. Dolin RH, Alschuler L, Beebe C, et al. The HL7 Clinical Document Architecture. *J Am Med Inform Assoc JAMIA*. 2001;8(6):552-569.
49. Index - FHIR v4.0.1. Accessed May 11, 2022. https://www.hl7.org/fhir/
50. Roosan D, Chok J, Baskys A, Roosan MR. PGxKnow: a pharmacogenomics educational HoloLens application of augmented reality and artificial intelligence. *Pharmacogenomics*. 2022;23(4):235-245. doi:10.2217/pgs-2021-0120
51. Roosan D, Hwang A, Roosan MR. Pharmacogenomics cascade testing (PhaCT): a novel approach for preemptive pharmacogenomics testing to optimize medication therapy. *Pharmacogenomics J*.

2021;21(1):1-7. doi:10.1038/s41397-020-00182-9

# Figures

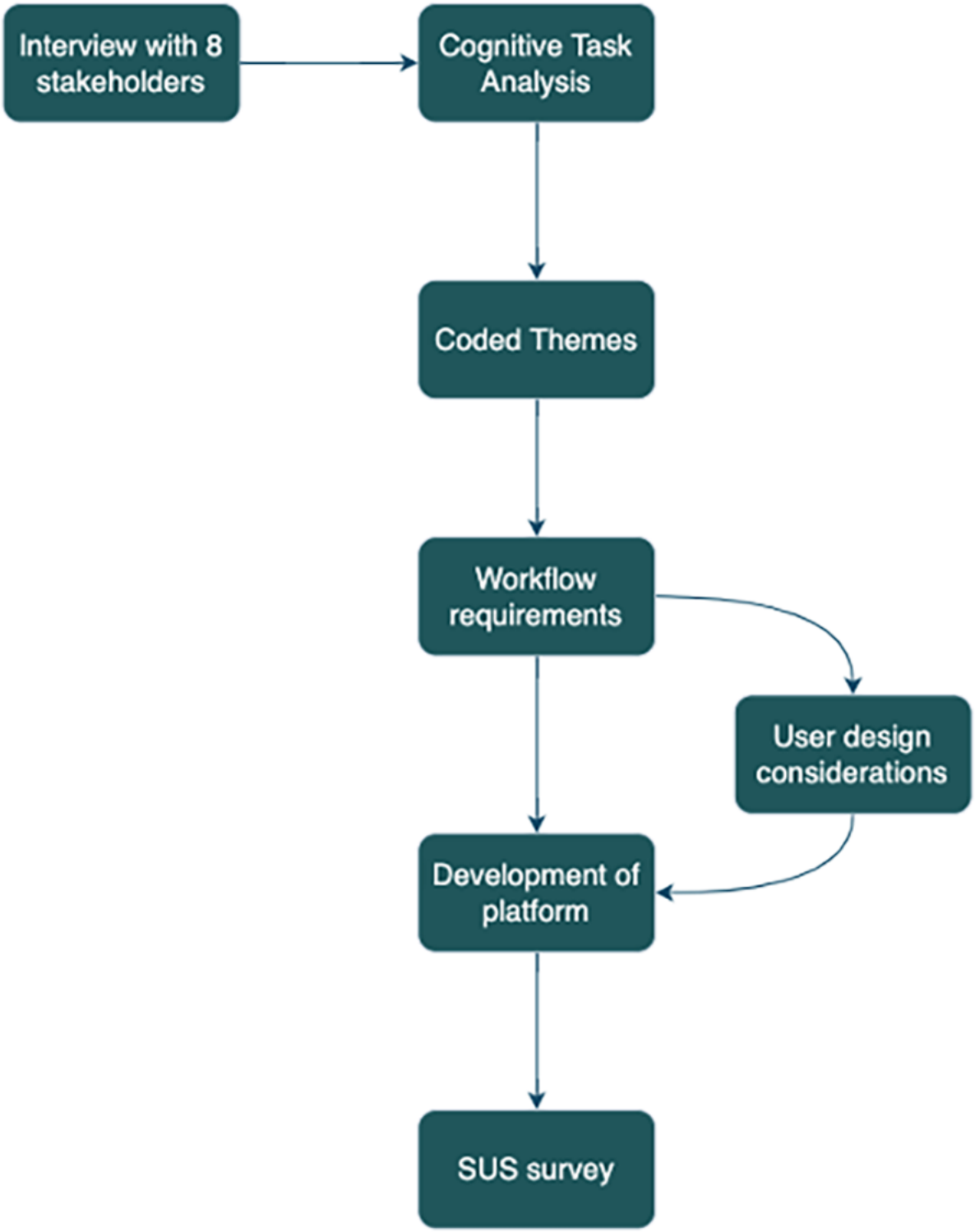


**Figure 1**

**Flowchart of methods starting with stakeholder interviews and ending with surveys.**

The flowchart shows the overall methodology for conducting cognitive task analysis and using the data to create recommendations for user-centered design finally.

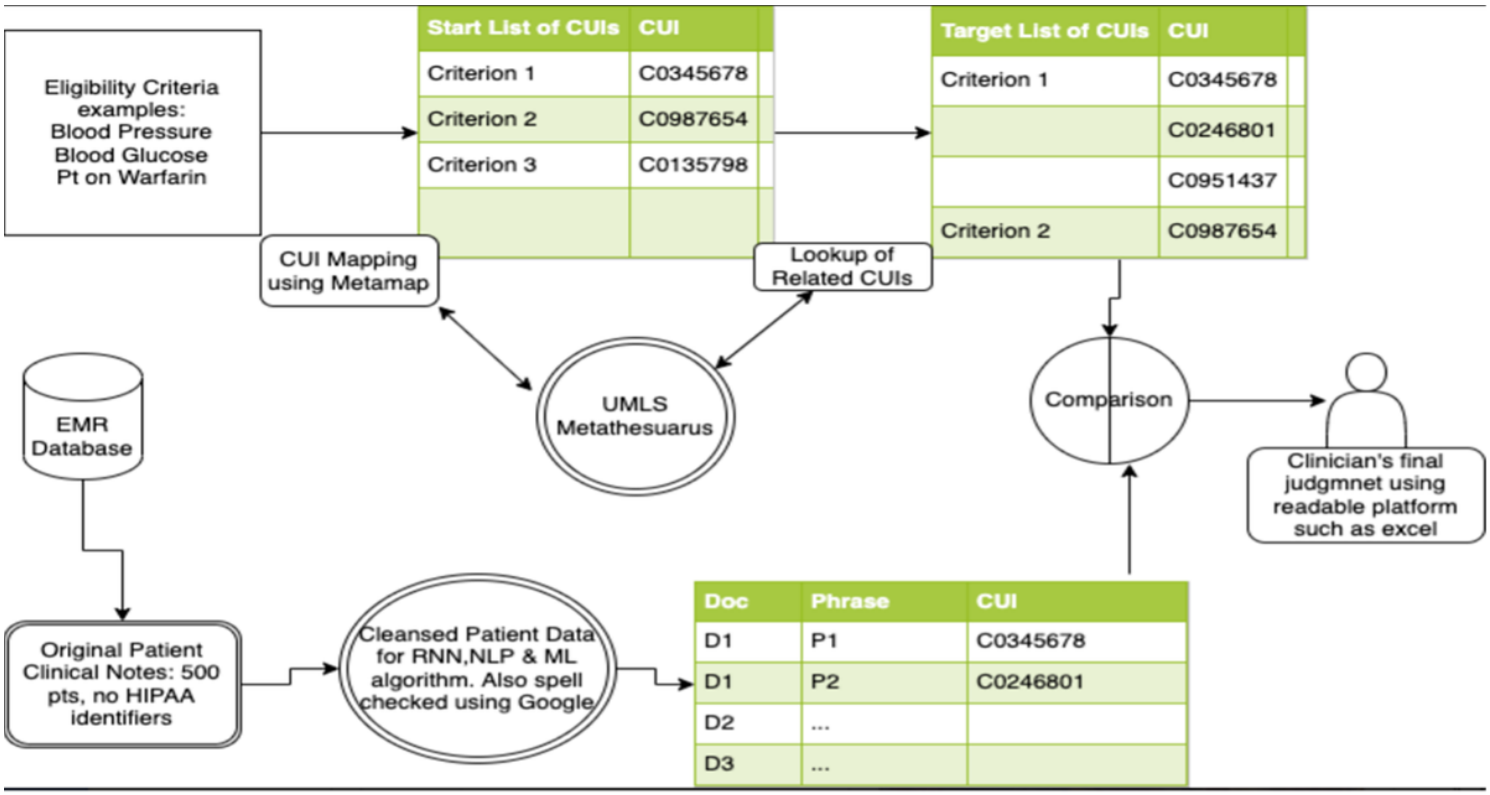


**Figure 2**

**Overall process of creating the Artificial Intelligent algorithm**

The specific words were parsed based on eligibility criteria, and a specific CUI number was given. From the CUI, we used the RNN, NLP and CRNN algorithm, which provided phrases. Finally, we compared the phrases to ensure they were the same and showed them to clinicians.

**Figure 3**

**Snapshots of the platform in observing and analyzing patient-related information**

(a) Patient lab value trends and visualization. (b) A trend of patient vitals. (c) Search results for blood pressure >120 with 4 patients matching criteria. (d) Search results for warfarin and resulting ratios of 14 patients on warfarin and active problems from warfarin

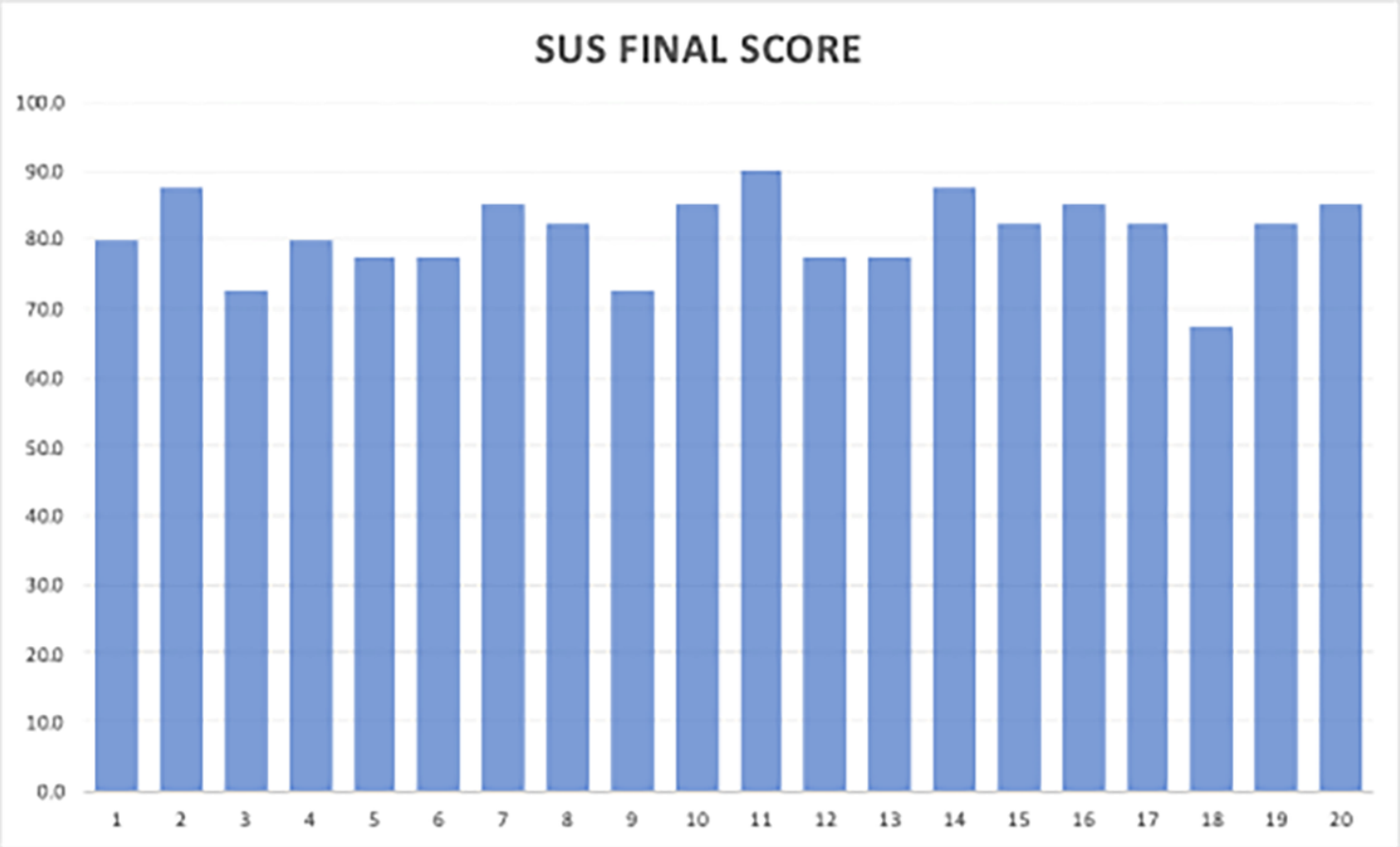


**Figure 4**

**SUS individual final scores of 20 participants**

The SUS scores show a total of 20 participants and their SUS scores