Hands-Free Electronic Documentation in Emergency Care Work through Smart Glasses

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Abstract. As U.S. healthcare system moves towards digitization, Electronic Health Records (EHRs) are increasingly adopted by medical providers. However, EHR documentation is not only time-consuming but also difficult to complete in real-time, leading to delayed, missing, or erroneous data entry. This challenge is more evident in time-critical and hands-busy clinical domains, such as Emergency Medical Services (EMS). In recent years, smart glasses have gained momentum in supporting various aspects of clinical care. However, limited research has examined the potential of smart glasses in automating electronic documentation during fast-paced medical work. In this paper, we report the design, development, and preliminary evaluations of a novel system combining smart glasses and EHRs and leveraging natural language processing (NLP) techniques to enable hands-free, real-time documentation in the context of EMS care. Although optimization is needed, our system prototype represents a substantive departure from the status quo in the documentation technology for emergency care providers, and has a high potential to enable real-time documentation while accounting for care providers' cognitive and physical constraints imposed by the time-critical medical environment.

Keywords: Smart Glasses, Documentation, Electronic Health Record, Natural Language Processing, Emergency Medical Services

1 Introduction

As U.S. healthcare system moves towards digitization, Electronic Health Records (EHRs) have been widely adopted by medical providers. However, documenting patient data using EHR systems is a challenging and time-consuming task as it demands a significant portion of care providers’ time and cognitive attention. Prior work has pointed out that the use of EHRs could lead to physician burnout, reduced patient care time, and compromised patient-physician relationships [1, 2]. In time- and safety-critical medical settings, such as emergency medical services (EMS) or pre-hospital domain, these challenges are exacerbated due to the dynamic, rapid, and high-stress nature of patient care in the field, making the use of EHR systems challenging [3, 4]. For example, since EHR systems are often implemented on handheld devices, such as tablets, EMS providers may not be able to use such devices in real-time as they need to perform hands-on care to stabilize critical patients while processing various information and making sense of what they face [5-8]. Also, switching between patient and EHR could increase the chance of cross-contamination [9]. As such, jotting down notes on temporary artifacts, such as gloves, persists in EMS work practice [8, 10]. This workaround, however, is a barrier to implementing real-time clinical decision support systems. Therefore, it is more than evident that novel technologies are necessary to support real-time EMS documentation.

Prior work suggested that smart glasses—wearable technologies that superimpose information onto a field of view through transparent heads-up display—can potentially serve as an unobtrusive hardware platform to support timely documentation as they offer novel interaction techniques (e.g., voice control) [11-13]. They can be connected with EHR systems and vital signs monitor to facilitate information sharing and enable an integrated view of patient status. Since their introduction several years ago, smart glasses have been tested and used mainly as a telemedicine tool in various medical settings, such as surgical tele-mentoring [14], remote evaluation of acute stroke patients [15], and disaster telemedicine triage [16, 17]. The "hands-free" capability of smart glasses makes this technology of interest to EMS providers [18, 19]. However, to date, limited research has investigated the application of smart glasses in supporting real-time documentation during pre-hospital encounters.

To that end, we conducted an exploratory study to design and develop a smart glass application to automate EMS documentation. More specifically, we first conducted user studies with 13 EMS providers to elicit system requirements (section 4.1). The findings of user studies informed the design of our smart glass application, including system features, interaction mechanisms, and system architecture (section 4.2). Then we developed a system prototype that leverages natural language processing (NLP) techniques to process domain-specific, voice-based dictations (section 4.3). Lastly, we conducted preliminary evaluations with EMS providers to measure system accuracy and gather user feedback (section 5). To the best of our knowledge, this is the first smart glass system prototype developed to support documentation in time-critical medical settings. We conclude this paper by discussing lessons learned, limitations, and future work.

2 Related Work

In this section, we first review a set of literature on the use of electronic health records in time-critical medical settings to highlight research gaps. Then we discuss existing research on the application of smart glasses in medical work to highlight the novelty of this technology and its promising potential in supporting clinical documentation.

2.1 Electronic Health Records in Time-Critical Medical Settings

As prior work pointed out, the use of EHR systems in fast-paced, safety-critical medical settings could lead to decreased patient care time, inefficiencies, and incomplete data entry [20]. One main reason for these issues is the mismatch between the formal EHR documentation and actual clinical workflow, making it nearly impossible to complete numerous EHR data fields in a timely fashion [21, 22]. For example, in trauma resuscitation settings, Jagannath and Sarcevic [23] found that only 8% of verbally reported information was documented in near real-time, while 42% of verbal reports were not documented in the EHR system. Also, information was documented with a delay, which can be attributed to the current layout of the EHR system used by trauma teams, that is, the data fields were grouped following logical rather than context-driven structure [23, 24].

Our study context—EMS—faces even greater challenges because unlike other clinical teams which usually have a designated person (e.g., nurse recorder) in charge of documentation [25, 26], EMS teams do not have a dedicated role for the documentation task. EMS providers are constantly on the move at the point of accident while performing hands-on tasks to address life-threatening injuries or illnesses, leaving them with limited ability to use an EHR system in real-time [5, 10]. Even when used, EMS documentation is prone to erroneous and incompletion. For example, a study found that 40% of the data entered on EMS medical records were either left blank or filled in erroneously [6], while another study reported that 28% of EMS records were missing patient's physiological data values [7]. As pointed out by several studies [3, 4], many of these issues were caused by the gap between data entry methods and EMS workflow—complicated data entry across too many screens increased the cognitive and physical burden of using EHR [10]. It is, therefore, more than evident that novel technologies and modes of interaction are needed to improve data collection and documentation in time-critical and hands-busy critical care environments. Although some studies examined ways to automate the information extraction from the EHR clinical notes [27-29], few research has investigated how to facilitate and automate real-time data collection and documentation in fast-paced medical environment [30, 31]

2.2 Smart Glasses in Medical Work

Smart glasses have gained momentum in recent years because they offer hands-free operation through novel interaction mechanisms such as voice control [12, 13, 32, 33]. With a transparent screen and a video camera, smart glasses enable constant information presentation and allow local workers to project first-person point-of-view to a remote viewer. Given these benefits, researchers are increasingly interested in using smart glasses to support medical work, such as care management [13, 34-36], surgical tele-mentoring [14], disaster telemedicine triage [16, 17], and vital sign monitoring [18]. For example, one study [11] explored the feasibility of using smart glasses to capture visual information of a patient's wound and transfer it to the patient's EHR record through gestural and voice commands. Despite this prior work, how smart glasses can support real-time documentation during fast-paced medical work remains unanswered. In this study, we aimed to bridge this knowledge gap by designing and developing a smart glass application to augment real-time data capture and documentation.

3 Methodologies

3.1 Data Collection and Evaluation of System Prototype

We first conducted semi-structured interviews with 13 EMS providers recruited from four hospital-based EMS agencies in the U.S. Northeast region to elicit user needs and opinions for using smart glasses to facilitate their documentation task. The interviews focused on the challenges faced by EMS providers in collecting, documenting, and sharing patient data in real-time during pre-hospital encounters, and how smart glasses can help address these challenges. Based on the results of this user study, we designed and developed our system prototype.

We also conducted preliminary evaluations of our system. More specifically, we recruited two experienced EMS providers who have more than 30 years of experience to measure the accuracy of our system in processing and automatically documenting medical information. We also presented our prototype to 10 EMS providers who participated in the previous interview study. Following the presentation, we asked the EMS providers to express their opinions and concerns, identify unmet needs, and discuss opportunities for further improvement.

All interviews and evaluations were audio recorded and transcribed verbatim. The study was approved by the first author's university Institutional Review Board.

3.2 Data Analysis

We used an open coding technique [37] to analyze the transcripts. Two researchers generated and discussed a list of codes in an iterative manner until consensus was reached. Then the researchers used affinity diagrams—a common approach for finding patterns in the qualitative data [38]—to group all the codes under themes. This step allowed the researchers to identify high-level themes describing user needs regarding the use of smart glasses for automated documentation, and opinions and concerns about using the system in practice.

4 System Design and Development

In this section, we first describe the major technology requirements emerged through user studies, followed by an overview of the design of our system prototype. Lastly, we provide detailed description of how we leveraged NLP techniques to automate domain-specific information processing and documentation.

4.1 User Requirements

Through the interviews, four major technology requirements emerged, the details of which are described as follows:

1) *Facilitate rather than replace the use of current EHR system*. As we learned from the discussion with EMS providers, the system should be designed to facilitate their documentation task instead of replacing current EHR system used in practice. As such, the smart glasses should be connected with an EHR system and function as a "facilitator" to quickly collect and integrate patient data and transfer that into EHR to reduce the time spent working on documentation. To achieve that goal, the system should allow EMS providers to dictate patient information to the smart glasses and have the smart glasses transcribe the dictation in real-time to text through voice recognition. Also, the system should be able to parse and extract key medical information from the transcript and populate the corresponding data fields in EHR.

2) *Enable the "hands-free" paradigm of using smart glasses*. The default interaction technique is using the built-in touchpad and buttons to navigate the user interface embedded on the transparent heads-up display. However, this interaction modality requires physical touching and clicking on the device, which EMS providers would want to avoid. As such, participants expressed interest in using hands-free interaction mechanisms to interact with smart glasses.

3) *Allow timely collection of medication information*. Collecting and documenting accurate medication information is a challenging and time-consuming task, especially under extreme time pressure. EMS providers expressed interest in being able to use the smart glasses to scan the barcode of the medication given to the patient so that the detailed information of the medication (e.g., name, dosage, etc.) can be automatically captured and saved to EHR. In addition, since some patients could take several medications due to, i.e., comorbidities, but EMS providers may not have sufficient time to complete detailed entry for each medication using EHR, the medication scanning feature enabled by smart glasses could also make the collection of patient's medical history much easier.

4) *Ability to record and store visual information*. In most cases, EMS providers need to share information with the care providers in the receiving hospital (e.g., emergency department physician and charge nurse) en route to the hospital or during patient handoff. When doing so, EMS providers usually need to spend a significant amount of time describing the patient situation and mechanism of injury (e.g., what happened, how severe the accident was) with words. Aligning with previous work [39, 40], our participants mentioned that this practice is not only time-consuming but also vulnerable to miscommunication. Therefore, participants would like to use the smart glasses to take pictures or record short videos so that they can share such visual information with the receiving care team.

4.2 System Architecture

As our major goal is to augment rather than replacing the use of EHR during EMS care, we integrate the smart glasses with the EHR system used by EMS providers. Our system prototype consists of a pair of Vuzix M400 smart glasses, an Android-

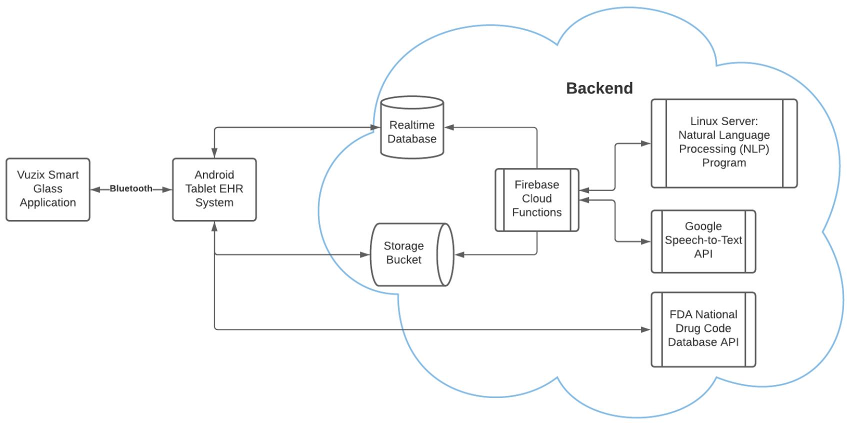

Figure 1. System architecture

based EHR system, and a cloud-based backend (Figure 1). The major functionality of this system prototype is allowing EMS providers to dictate patient information to the smart glasses and have the smart glasses transcribe the dictation in real-time to text, which will be saved in the "Narrative" section of EHR. Then, the system can process the transcribed narrative and extract key medical information to be saved into the corresponding EHR data fields.

The Vuzix M400 is an ergonomically designed wearable device. It runs using an Android 9.0 based operating system. The camera on the device allows for still image capture or video recording, which can be saved for further use (e.g., sharing with the emergency care teams at the receiving hospital). Our application will allow the user to scan medical barcodes to capture information about patient treatments and medication. This is done by utilizing the National Drug Code database in the OpenFDA API. The device also has a transparent heads-up display, on which computer-generated or digital information can be overlaid and seen by the users. By default, users can use the touchpad and buttons to navigate the user interface (Figure 2). But smart glasses can also offer hands-free user interaction through other novel mechanisms, such as voice commands and hand gestures. For example, we implemented voice commands (e.g., "take a picture," "dictate," etc.) using the Vuzix software development kit (SDK), and gesture-based controls using a third-party SDK (CrunchFish[1]).

Since we need an EHR system for testing purposes, we developed a hypothetical, simplified EHR application based on a real system. This EHR application runs on Android mobile devices (e.g., a tablet) and contains five major sections to organize and record patient information (e.g., incident, demographics, assessments, vitals, and narrative), with each section contains a set of data fields.

[1] https://www.crunchfish.com/.

Figure 2. Interacting with smart glasses via the built-in touchpad

The backend of our system consists of a Firebase real-time database, a storage bucket, Firebase cloud functions, and an external Linux server running our text analysis program. All application data regarding patient records are stored in the real-time database. Audio files created through dictation are stored in the storage bucket and the cloud functions monitor the bucket for new audio files. When the user completes a dictation, the audio file is saved and then transcribed using the Google Cloud Speech-to-Text API. When the transcription is completed, the text is written to the database and saved to the "Narrative" section on EHR. Afterward, the system makes a request to the Linux server running a program for text analysis (see section 4.3). The textual analysis program utilizes a set of NLP techniques to extract medical concepts and return data that is categorized for each field of the EHR. Upon successful processing, the data produced will be written to the database and updated on the EHR application simultaneously, and the user will be able to review and make any necessary changes before closing out the patient record.

4.3 Automating Information Processing and Extraction from Transcribed Narratives

As the major functionality of our system prototype is allowing EMS providers to dictate to document patient data, in this section, we focus on describing how we implemented this feature to automate the extraction of domain-specific information from transcribed dictations. As shown in Figure 3, we built an unsupervised NLP framework which consists of four major components: UMLS MetaMap [41], syntactic analysis [42], pattern matching, and Med7 [43]. The UMLS MetaMap is a tool developed by the U.S. National Library of Medicine (NLM), which makes use of various biomedical sources to map the phrases or terms in the input text to different semantic

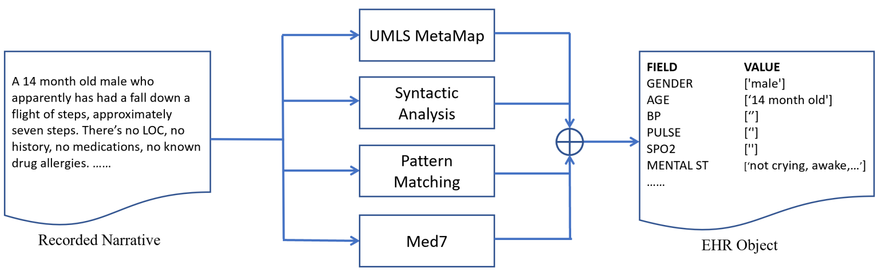

Figure 3. Unsupervised NLP framework for information extraction

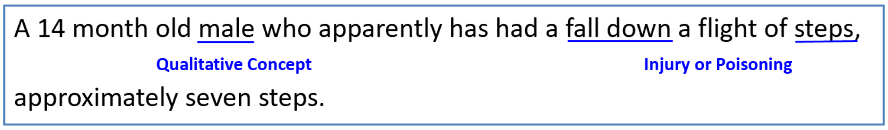

Figure 4. Example of MetaMap processing and semantic types

types. Figure 4 provides an example of mapping phrases to different semantic types using MetaMap. We used a set of semantic types of UMLS MetaMap to identify the relevant concepts to the EHR fields. For example, semantic type ‘Body Part, Organ, or Organ Component’ is used to identify whether a chunk of text mentioned lung, pupil, or any body organs. Then, the syntactic dependency tree generated by Stanford CoreNLP [44] is used to extract the information describing the conditions of the body organs or mental status. The negation detection and word sense disambiguation of MetaMap are configured to recognize negation context and determine the best matching sense of the concepts within the context. Pattern matching is a rule-based approach to identify gender information, blood pressure values, etc. Med7 is a refined named-entity recognition model which is mainly used to identify medication-related information mentioned in the dictation, such as medication names, route, usage frequency, suggested dosage, strength, form, and duration.

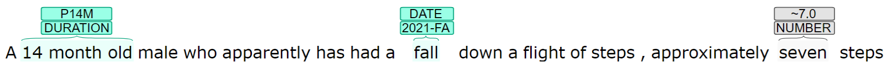

Figure 5. Name entity recognition using Stanford CoreNLP

In this exploratory project, we demonstrate the feasibility of extracting information to populate 23 EHR data fields using the designed NLP framework, including gender, age, blood pressure (BP), pulse, oxygen saturation (SPO2), respiration rate (RESP), blood glucose levels (B.G.L), Glasgow Comma Scale (GCS), mental status, patient condition, patient medication, allergies, past medical history, pain, trauma scale, pupils, lung sounds, verbal, airway, injury, mechanism of injury, complaint, and treatment. Below we describe the information extraction techniques we used for each data category in greater details.

***Age*:** To recognize patient age mentioned in the description, we used the name entity recognition module in the Stanford CoreNLP [44]. If a text is tagged as "Duration" with "PXX", shown in Figure 5, it is extracted as age. “PXX” is the tag for person (P) entity with age value “XX”. In this example, the age value is 14M – 14 months.

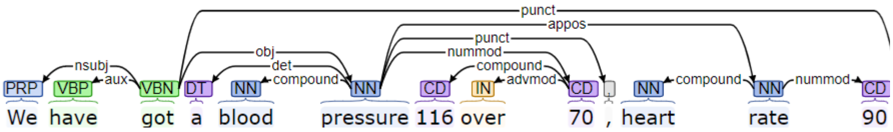

Figure 6. Syntactic dependency analysis

***Gender, BP, SPO2, RESP, B.G.L, GCS, Verbal, Trauma scale and Airway*:** We used pattern matching and syntactic dependency tree analysis to extract the information for these categories. First, we defined a set of terms for each field that are often used by EMS, such as “blood pressure” and related abbreviations for BP, to locate the relevant information within the context. Then, a set of regular expression rules based on the patterns and syntactic dependencies between the terms are used to extract the associated values for the fields, if there are any. As shown in Figure 6, once “blood pressure” is identified using pattern matching rules, then syntactic dependency tree is used to identify whether there is a number tagged as Part-Of-Speech tagging “CD” has a direct or indirect dependent relation with one of the words in “blood pressure”. If yes, regular expression is used to extract the numbers of the blood pressure. It is worth noting that since the recorded narratives are in spoken language, EMS providers may not necessarily follow the strict grammar. Hence, we also specified an additional set of regular expression rules to identify the numerical values corresponding to these fields when there are no dependent relations between the term and the corresponding numerical values.

Table 1: MetaMap semantic types used for the selected EHR fields

EHR Fields	**Semantic Types**
Mental Status, Patient condition, Complaint	Finding
Lung sound, Pupil, Injury	Body Part, Organ, or Organ Component
Treatment	Clinical Attribute, Clinical Drug, Medical Device
Allergies	Finding, Pathologic Function
Pain	Sign and Symptom
Injury, Mechanism of Injury	Injury and Poisoning

***Mental Status, Patient condition, Complaint, Lung sound, Pupil, Allergies, Pain, Treatment, Injury, and Mechanism of Injury*:** To process information for these fields, we first used MetaMap to identify the concepts of selected semantic types that are relevant to them. Then, we applied syntactic analysis to retrieve the context describing the status or conditions for these fields. Table 1 lists the MetaMap semantic types used for each field.

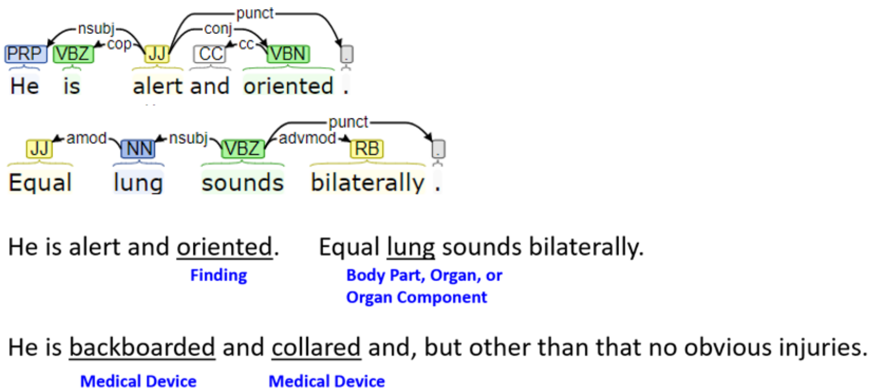

Figure 7. An example to demonstrate the use of MetaMap with syntactic analysis

Since not all concepts tagged as semantic type ‘Finding’ is relevant to mental status or patient condition, we specified a set of terms often used by EMS providers and then refined the terms using syntactic dependency analysis to retrieve additional words that are syntactic modifiers or connected by conjunctions. Given the example in Figure 7, the ‘alert and oriented’ is categorized as mental status. The ‘oriented’ is tagged as ‘Finding’ by MetaMap and it is in the set of terms we specified. The 'alert' is also extracted since there is a conjunction relation between 'alert' and 'oriented'. The 'equal' is extracted for lung sound field because 'lung’ is identified by MetaMap as semantic type ‘Body Part, Organ, or Organ Component’, and there exists a modifier relation, such as adjective modifier (amod), between ‘equal’ and ‘lung’. Lastly, 'backboarded' and 'collared' are both extracted as treatment since they are tagged as semantic type 'medical device' by MetaMap.

***Past medical history*:** The patient’s past medical history refers to chronic health conditions or surgeries that the patient has had previously. From the transcribed narrative, the information about past medical diseases or statuses is first located using MetaMap semantic types ‘Finding’, ‘Clinical Attribute’, ‘Clinical Drug’, and ‘Disease or Syndrome’. Then, syntactic dependency is analyzed to confirm whether the described medical history is relevant to the patient.

***Patient Medication*:** This data category refers to the medications taken regularly by the patient as part of their care management, e.g., treating chronic conditions. We used Med7 to extract all the detailed medication information from the narrative. Then, syntactic dependency analysis is applied to confirm whether the medication is taken by the patient or given by the EMS practitioners. Given the example in **Error! Reference source not found.**, we first identified ‘metformin’ using Med7. Then through dependency analysis, we found that metformin is indirectly linked to ‘patient’ through the verb ‘taken’. Hence, ‘metformin’ is extracted as patient medication.

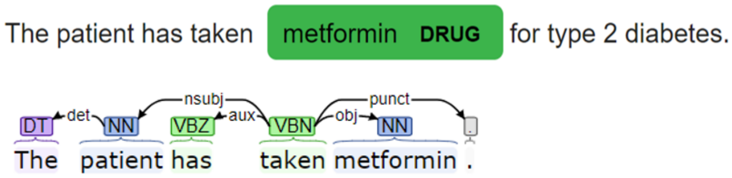

Figure 8. An example of utilizing Med7 and syntactic analysis for medication extraction

5 Preliminary Evaluation

In this section, we describe the preliminary evaluations of our system prototype, including the accuracy of automated documentation and end-users' perceptions of using the system.

5.1 Measuring the Accuracy of Automated Documentation

Table 2 Inter-rater reliability results

EHR Field	Cohen kappa	EHR Field	Cohen kappa
Age	1	Past medical history	0.944
Gender	0.889	Pain	0.889
BP	0.944	Trauma scale	0.780
Pulse	0.944	Pupils	0.944
RESP	0.889	Lung Sound	0.944
B.G.L	1	Verbal	0.889
SPO2	1	Airway	0.889
GCS	1	Injury	0.726
Mental Status	0.512	Mechanism of injury	0.460
Patient Condition	0.304	Complaint	0.726
Current Medication	0.889	Treatment	0.780
Allergies	1		

The performance of the system, especially the accuracy in processing and extracting medical information from narratives, was evaluated independently by two experienced EMS professionals. Each evaluator was given 19 processed narratives and asked to evaluate the accuracy of each extracted information based on the content of the original narrative. For each field, the evaluator needs to provide an answer as to whether the extracted information is correct or not. If it is incorrect or partially correct, the evaluator was asked to provide the correct information that should be ex-

tracted. Based on the expert inputs for all EHR fields extracted from the 19 narratives, Cohen's kappa value for each field was calculated to measure inter-rater reliability (**Error! Reference source not found.**). Based on the results, we can see that the inter-agreement between two evaluators is high on most of the fields when the extracted value is a number or some straightforward content, such as "clear" for airway. However, the inter-agreement is
not optimal when the extracted value is expected to be a more complex description, such as patient condition and mental status.

To calculate the system performance, we used the fields of all narratives for which both evaluators have the same evaluation, which means they either both agree the extracted value is correct or incorrect. If they both agree that the extracted value is incorrect and provide the same correct information, the information provided by evaluators is used as ground truth. Two different evaluation metrics were used: exact match (EM) and fuzzy partial match (FPM) [45]. These metrics are often used in information extraction and name entity recognition tasks [46, 47]. The exact match counts an extracted field is correct only if the extracted content matches the ground truth exactly, whereas fuzzy partial match score measures the differences between the extracted content against the ground truth at the word level. Given a narrative *"…my patient is awake and alert, no crying, but he does smile and interact. 15 on GCS, he's got good pulse…*", the extracted mental status is "*awake and alert*", but the ground truth given by the evaluators is "*awake and alert, no crying, does smile and interact*". It is counted as incorrect if exact match is used but counted as partial correct with a fuzzy partial score. The fuzzy partial match score [48] is calculated using the fuzzy string matching based on Levenshtein distance [49]. The fuzzy ratio score is calculated using Equation 1, where |A| and |B| are the lengths of string A and B, and L is the Levenshtein distance between A and B.

$$\frac{|A| + |B| - L}{|A| + |B|} \qquad (1)$$

The fuzzy partial score is calculated by first finding the best matching sub-string between A and B. Then it calculates the ratio score between the sub-string and shorter string among A and B.

Figure 9 shows the performance evaluation using the average FPM and SM scores of all narratives on each field. The results show that for age, gender, B.G.L, SPO2, allergies, past medical history, and airway, our system can extract all the values correctly from the narratives. However, for mental status, patient condition, and mechanism of injury, the system gains relatively low FPM and SM scores. We also noticed that the inter-agreement values for those fields are not high, which means the information to be extracted for those fields varies based on human's understanding of the narratives. For example, given the following narrative, the first evaluator identified the patient mental status as "patient is awake and alert, not crying, but he does smile, and interact", whereas the second evaluator extracted "not crying, awake, alert, had started acting lethargic". The identified content by both evaluators is similar semantically, although not exactly the same.

"*A 14 month old male who apparently has had a fall down a flight of steps, approximately seven steps. there's no LOC, no history, no medications, no known drug* *allergies. Our patient, came home, he was over at a friends house, he was brought back home, and apparently, had started acting lethargic and started shaking and convulsing. at this time, my patient is awake and alert, not crying, but, he does smile, and interact. 15 on the GCS, he's got a good pulse, everything's good. Little bump on the head, on the front of the head. he is backboarded and collared and, but other than that no obvious injuries*."

The output of our system for patient mental status in the above narrative is "not crying, awake, alert, no LOC, had started acting lethargic and started shaking and convulsing". Compared with the identified content by both evaluators, our system successfully extracted most information related to patient mental status. However, according to the evaluators, "no LOC" and "started shaking and convulsing" should not be considered and extracted as part of the mental status. Nevertheless, our system was deemed to perform well in processing narratives to extract medical information to

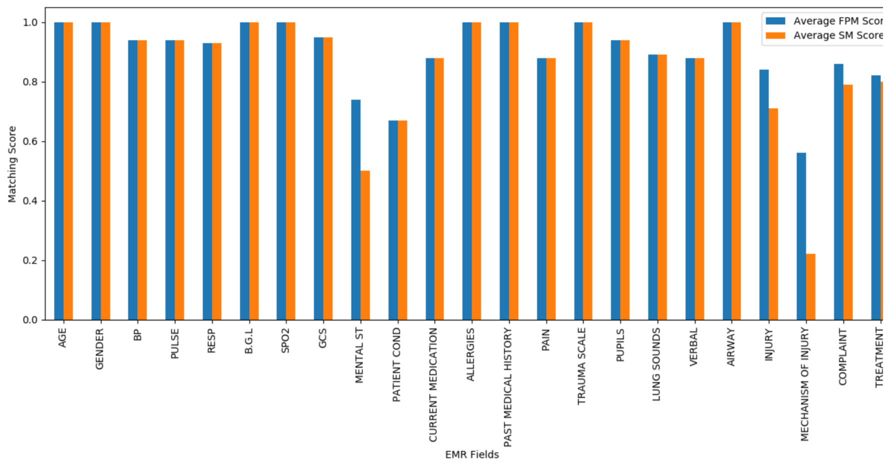

Figure 9. System performance on information extraction

be saved in corresponding EHR data fields, despite optimization is needed.

5.2 User Perceptions and Concerns

We also presented our system prototype to EMS providers (n = 10) to elicit their feedback. All participants considered our system useful in supporting their documentation tasks. Almost all of them (9 out of 10) expressed the willingness to use this system given its potential benefits: "*I think that would be very beneficial because it frees up our hands to do almost everything. If I would be able to say to narrative, I think that would be very helpful because that frees up not only one care provider, but two, so that two people can work on their patient and expedite the patient's care, which leads to a better patient outcome*." [P7]

In addition, our participants believed that being able to document patient data in real-time could also facilitate patient handover between EMS providers and emergency care providers in the receiving hospital. As one participant explained: "*It saves* *time. When you get a trauma patient to the hospital, we have to stand in the middle of the emergency room or in the trauma bay, and we have to go over what happened to the patient and what we did step-by-step like at least three times because somebody is always walking in who wasn't there when we were giving our verbal report. If we can get the documentation relayed to the emergency doctor before we arrived, they can just play a voice record or read through our documentation, and they would have all of our primary impression regarding how we found the patient and all such. Everything would be right there for them and that could save a lot of time*." [P7]

Despite the positive attitude, our participants shared some concerns in using this application in practice. First, pre-hospital environment is often very noisy, posing significant challenges in the effective use of the voice recognition feature of our system: "*The only thing that I am curious about is how sensitive it is to noise. For example, I have a patient who is yelling, and I am trying to dictate to document. How accurate will that be?*" [P9] Second, the work pace in EMS is very rapid, especially when patient acuity is high. In such cases, EMS providers are often both physically and cognitively overwhelmed as they need to multi-task—observing the scene, talking to partners or remote experts, while performing hands-on patient care tasks. As such, one participant had doubts about whether they can use the smart glass device in real-time: "*If I have somebody who got shot four times and I am trying to stabilize him, I'm not going to mess with that device [smart glass]. I wouldn't even bother documenting right away. I got to stabilize this person and after I get them stabilized, then I'll worry about the paperwork. […] But I definitely see the benefit of it in jobs that are not crazy and hectic*." [P11] However, this participant further explained that if there are multiple EMS providers on the scene in a high acuity situation, it is still possible for an EMS provider to use the smart glass device: "*If you are going to have two EMTs and two paramedics, not everyone is going to be doing all patient care. If any of these people that are on that scene can use a set of the smart glasses and just start getting information imported to the [EHR] data fields, I could see that being a huge benefit*." [P11]

6 Discussion

The system prototype we developed allows EMS providers to complete documentation in real-time while accounting for their physical ability to use computing devices. Instead of replacing current EHR systems, our goal is to facilitate the use of EHR for real-time data collection and documentation through smart glasses. As such, we integrate smart glasses with EHR to allow EMS providers to dictate to smart glasses in a hands-free manner. The dictations then can be transcribed and processed to populate the data fields on EHR automatically. By doing so, the documentation work in time-critical medical settings that is often vulnerable to delayed or erroneous data entry can be semi-automated, thereby saving a significant amount of emergency care providers' time and effort.

Although a number of studies focused on developing techniques to automate the information extraction from the EHR clinical notes [27-29], few research looked at how to facilitate data collection and decision making in emergency medicine [30, 31]. To the best of our knowledge, our research is the first attempt at automating EMS documentation. This work is essential in that it can enable the deployment and use of decision support tools in EMS if real-time data collection and documentation can be accomplished. However, using smart glasses in EMS context has some challenges to overcome [50]. For example, the noisy and interruptive nature of the field could pose challenges in the effective use of the voice recognition feature of smart glasses. In recent years, novel techniques have been developed to address this issue, such as sensing and signal processing solution that enables high performance of automatic speech recognition of smart glasses [51]. To fully realize the use case of smart glasses in automating EMS documentation, future research is needed to systematically test the performance of smart glasses in transcribing medical procedures while EMS providers perform them in noisy, dynamic, and fast-paced environments.

Regarding our underlying NLP framework for EMS concepts extraction from transcribed narratives, one of the major challenges is the lack of EMS lexicon, annotated data, or ontology. Hence, it is difficult to systematically apply EMS domain knowledge or supervised information extraction algorithms. In this research, we choose to use unsupervised learning, with which we successfully extract the values for most data fields, including complex clinical information (e.g., treatments). However, we found that it is challenging to extract information for the fields that often contain longer and domain-specific content, such as mental status. In this research, we utilized a set of EMS terms to first locate the mental status content within the whole narrative, and then extract the negation words or dependent words to those EMS terms. The limitation of this approach is that if some terms or jargon used by EMS are not included in our list, we could miss the relevant content. On the other hand, through the dependency analysis, we might introduce words that are not standard terminologies in the EMS domain, although they are used to describe patient status. Hence, it is very important to incorporate the EMS domain knowledge, i.e., through building an EMS ontology, to optimize our NLP framework. More specifically, we will leverage the narrative data in the National EMS Database [52] to build an ontology to include the terminologies often used in the EMS domain for better information extraction. We will also create an annotated data set for the EHR fields with various and complex content, so that we can train supervised deep language models [53, 54] for those content recognitions.

Lastly, as shown in Table 2, the inter-agreement scores of some categories with long and complex descriptions, such as patient condition, are relatively low. This is because we applied word-based matching to calculate the inter-agreement scores. The calculation could be changed to segment based semantic matching, which means if the semantic similarities between segments of the annotations are high, the inter-agreement is high. Our system performance could also take advantage of the segment based semantic matching approach. Hence, instead of using the word level matching calculation, semantic based matching counts the correctness when the semantic meaning is very close. The semantic based matching could also improve the low performance categories listed in Figure 9.

7 Conclusion

In this exploratory study, we first conducted an interview study with EMS providers to elicit user perceptions and needs with respect to using smart glasses to support their documentation work. Based on the user studies, we designed and developed a smart glass application to automate documentation during pre-hospital encounters. We also performed preliminary evaluations to measure system accuracy and gather user feedback for further improvement. Although optimization is needed, our system demonstrates its high potential in enabling hands-free, real-time documentation for emergency care providers. Our future work includes systematic evaluations of system usability and performance, and improvement of our underlying NLP framework.

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