INDIANAPOLIS EMERGENCY MEDICAL SERVICE AND THE INDIANA NETWORK FOR PATIENT CARE:

EVALUATING THE PATIENT MATCH PROCESS

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This paper is dedicated to my loving wife Eunpa Jung. Without her support, encouragement, and prayer, I would not have the goals for this study and the ability to strive and be the best to reach my dreams.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

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ABSTRACT

Seong Cheol Park

Indianapolis Emergency Medical Service and the Indiana Network for Patient Care:

Evaluating the Patient Match Process

In 2009, Indianapolis Emergency Medical Service (I-EMS, formerly Wishard Ambulance Service) launched an electronic medical record system within their ambulances and started to exchange patient data with the Indiana Network for Patient Care (INPC). This unique system allows EMS personnel in an ambulance to get important medical information prior to the patient's arrival to the accepting hospital from incident scene. In this retrospective cohort study, we found EMS personnel made 3,021 patient data requests (14%) of 21,215 EMS transports during a one-year period, with a "success" match rate of 46%, and a match "failure" rate of 17%. The three major factors for causing match "failure" were (1) ZIP code 55%, (2) Patient Name 22%, and (3) Birth Date 12%. This study shows that the ZIP code is not a robust identifier in the patient identification process and Non-ZIP code identifiers may be a better choice due to inaccuracies and changes of the ZIP code in a patient's record.

CHAPTER ONE: INTRODUCTION & BACKGROUND

Background

Emergency medical services (EMS) play a critical role in the nation's emergency and trauma care systems. For 2009, there were an estimated 36,698,670 EMS events (responses) in the U.S., resulting in approximately 28,004,624 transports (McCallion, 2012). It is during these encounters where EMS personnel initiate care to patients and attempt to collect relevant information from the patient, such as chief complaint, past medical history, and current medications.

In circumstances where the patient is unable to provide relevant details: either obtunded from drugs or alcohol; or due to altered levels of consciousness from infection, metabolic reasons, or trauma, access to pre-existing medical information relating to medications, allergies, prior visits and hospitalizations, and diagnoses is even more critical when “time is of the essence” and may improve patient care.

Recent computer technology has offered greater capability of managing patient data to medical services including EMS. However, few EMSs across the country are using these kinds of new technologies, such as electronic medical record (EMR) in their ambulances. This lack of usage of current technology among EMS and hospital systems results in delays in patient care. This can be improved by using information technology, which allows EMTs to access pre-existing medical information of patients (Finnell & Overhage, 2010).

Since 2009, authorized EMS personnel of Indianapolis Emergency Medical Service (I-EMS) have been requesting patient data from the Indiana Network for Patient Care (INPC)(Finnell & Overhage, 2010; McDonald et al., 2005; J.M. Overhage, Tierney, & McDonald, 1995). This is the first regional health information exchange in the country to connect pre-existing health information to EMS providers. Previous study (Finnell & Overhage, 2010) illustrated the quantitative and perceived benefits of access to medical records by EMS providers in the pre-hospital setting.

As of 2005, Indiana Network for Patient Care (INPC) is a citywide clinical informatics network in cooperation with the Regenstrief Medical Record System (RMRS) throughout the broader population of the Indianapolis metropolitan area and the rest of the caregivers within the state of Indiana including 9 counties and the Indianapolis downtown area which is called the metropolitan statistical area (MSA). The INPC medical record system is working in all major health care systems within this MSA including Community Hospitals of Indianapolis, St. Vincent Hospitals and Health Services, St. Francis Hospital and Health Centers, Indiana University Health, and Wishard Health Services. Additionally, INPC includes 4 Marion County homeless care organizations, all county and state public health departments, primary care providers at 20 sites, 3,000 specialists, and 30 public school clinics. In brief, INPC members cover more than 95% of acute inpatient and non-office based outpatient clinical care within the MSA, including greater than 390,000 emergency room and 165,000 inpatient visits, and over 2.5 million clinic visits per year (Finnell et al., 2003).

INPC is managing tremendous data including 50 million laboratory results per year, all inpatient and emergency encounter summaries, such as admission and discharge summaries, operative notes, radiology reports, pathology reports, and inpatient medication data. In addition, the system exchanges public health data, including tumor and immunization registry data, with both the Marion County and Indiana State health departments (McDonald et al., 2005).

In collaboration with INPC, I-EMS is using mobile computer systems in their ambulances. EMS personnel initiate the patient identification (PI) process by submitting patient demographic data into their electronic medical record (EMR) (Medusa Medical Technologies Inc, 2009). Once the request is made, the system responds with a message that indicates whether a patient match is made in the INPC system and if a clinical abstract is forthcoming. When an INPC patient lookup request results in a successful match in the INPC system, a patient abstract PDF document is returned asynchronously to the EMS system and this abstract PDF document is added to the EMTs' patient care report automatically for future use. The medical information provided in the INPC EMS abstract allows pre-hospital personnel to collect a more detailed medical history and allows for more informed treatment decisions. (Eisenberg, Bergner, & Hallstrom, 1979)

As the system matured, there were incidents of situations where the EMS personnel would enter patient demographic data, yet no clinical abstract was returned from INPC indicating the result of no patient match found. However, upon arrival to the hospital, the patient was registered into the emergency department (ED), ED personnel did indeed have access to the clinical abstract, where the EMS personnel did not. These reports prompted us to investigate this further and to analyze the patient identification process between INPC and I-EMS including matching algorithm of the process in more detail.

The existing patient-matching algorithm is based upon the real world experience of matching patients across disparate hospital systems. While the current standard algorithm leverages the requesting institution name and patient medical record number along with other identifiers to match patients, I-EMS does not maintain a patient registry and therefore medical record numbers are not available in the patient identification process.

Purpose of the study

The purpose of this study is to evaluate the current patient identification process and to find the reasons why EMS personnel were unable to find the patient information from the INPC database in their ambulances, even though the patient does truly exist in the INPC when the medical staffs of accepting hospital ED enter the same patient information for getting the INPC abstract. The purpose of this study is three fold, (1) to identify current patient identification request rate between I-EMS and INPC within a certain time period, (2) to find success and failure rates among INPC abstract requests, and (3) to identify major factors that cause a failure in the patient identification process between I-EMS and INPC.

Significance of the Study

The patient identification process to identify patient medical records between different data sets is fundamental to the process of a health information exchange (HIE). It will allow healthcare stakeholders to share the information regarding provision of healthcare services without utilizing the same hospital information system (HIS). This study explores the current HIE process between I-EMS ambulances and hospitals and in result, the HIE process will provide appropriate care to patients without any medical complications and delays. Using hospital information technology (HIT) has shown positive effects on patient care with increasing patient safety by reducing medical errors and decreasing lead time to get appropriate treatments (Anantharaman & Swee Han, 2001).

Furthermore, an effective and efficient care plan can be established from the moment of care at the scene to discharge from the hospital based on acquiring correct medical records or history and providing appropriate information to healthcare providers, for instance EMTs, nurses, and physicians (Friedmann, Shapiro, Kannry, & Kuperman, 2006). J. Marc Overhage et al even found that there is a financial benefit from health information exchange between different emergency departments (ED). The study estimated a decrease in charges for ED care by approximately $26 per encounter (P=.03) at 1 hospital (J. Marc Overhage et al., 2002).

This patient data exchange system makes EMR data up-to-date with accurate and current information and allows this record to be used in future health related events. Eventually, this study will provide suggestions for future improvement of the patient identification process between INPC and I-EMS and a further research proposal for the patient identification process between INPC and I-EMS.

There are several studies that have been conducted in EMS with information technology, however, all data exchanges in previous studies are limited within the same hospital or single healthcare system (Mears et al., 2010; Petridou et al., 2009; J.S. Shapiro et al., 2006).

This is the first approach to try to connect different heath information systems through HIE technology. I-EMS has a unique system throughout the country which is able to connect EMS providers to pre-existing health care data which holds patient information from various hospital systems.

CHAPTER TWO: LITERATURE REVIEW

Studies have addressed the problems

There are several studies that focused on the patient data exchange process between hospital departments within the same hospital information system (HIS). Barthell et al., shows key components of data integration in emergency medicine. This report identified the obstacles of information technology in emergency medicine by adopting interoperable components to design the system. It suggests a list of recommendations to overcome, (1) early consideration of linkage between system components before the system design, (2) a data standard should be adapted, (3) standardized messaging should be used like HL7, and (4) hospital stakeholders should be collaborative, coordinated, and harmonized efforts to its IT system (Barthell, Coonan, Finnell, Pollock, & Cochrane, 2004).

Another study about HIE was conducted by Sauleau et al showing that multiplication of data sources between different hospital systems result in redundant information and split among multiple databases and it is important to identify duplicate records within databases in order to increase usability of the HIE system. This study showed the significance of duplicate-free databases, used in conjunction with relevant indexes and similarity values, which allow immediate (i.e.: real-time) proximity detection when inserting a new identity (Sauleau, Paumier, & Buemi, 2005)

These studies suggested that in order to use the hospital information system (HIS), the plan must start with early consideration of HI components and any health database needs to be managed without redundant data in it. These studies, however, are more focused on establishing HIS in general with design and management of HIS rather than finding the right identifiers to match the patient data and data matching process among hospital departments (Barthell et al., 2004; Boyle, 2008; Sauleau et al., 2005).

In data exchange in healthcare, Just et al, made some suggestions for clinical data exchange models with benefits and challenges of existing models. This study addressed that in order to get success in HIE systems, stakeholders must establish their primary goals for HIE. This also requires several processes including defining business level objectives; developing use cases to clarify the scenarios for exchanging clinical data, and describing the types of clinical data to be exchanged (Just & Durkin, 2008). More importantly, the authors addressed that stakeholders should consider "how a requested piece of clinical data (or report or record) will physically be delivered through the system" regardless of what model an HIE chooses.

According to a study from Friedman et al, the workflow of hospital setting, ED in this study, is the most important factor to affect the health information exchange in a hospital setting. This study found three types of workflows of EDs: paper-based, paperless (electronic record system), and a combination of paper and paperless. The ease of using the HIE system in the ED is dependent on its type of workflow in each clinical setting and the HIE has to be incorporated with existing workflow (Friedmann et al., 2006). Even though, Friedman et al, found critical aspects of workflow with the HIE system, its scope was limited within EDs in hospital and didn't account for actual data exchange between the ED and other departments within the hospital.

Regarding workflow, the New York Clinical Information Exchange (NYCLIX) was established to facilitate data sharing across 14 organizations. In this study, workflow evaluations revealed the identification mechanisms by which clinicians could be informed of NYCLIX data in the ED. The study interviews focused on the interval between patient arrival to the ED and clinician notification of a new patient arrival. In the results of study, there are three types of workflows in EDs, paper-based, paperless and using a combination of paper and electronic record (Jason S Shapiro, Kannry, Kushniruk, Kuperman, & Subcommittee, 2007).

Another study shows the challenges of health data exchange with identifiers. Wang et al conducted a study showing the challenges of exchanging and integration of patient data among heterogeneous databases; first, how to identify identical patients between different systems and institutions while lacking universal patient identifiers; and second, how to link patient data across heterogeneous databases and institutional boundaries. In order to solve these to challenges, Wang et al, created patient identification (ID). It created one methodology for overcoming challenges to find the right patient match among different databases (Wang & Ohe, 1999). This study introduced various methods to establish the right patient record match, but these cannot be applied to databases which are using different data records. It requires that existing databases need to be modified to have new "patient identification (ID)" in each patient record and it requires major changes and modifications in current database systems and new designs for new databases.

Regarding data exchange between ambulance and hospital, Anantharaman et al. showed that the majority of ambulance data was transmissible through patient data exchange systems between hospital and ambulance (Anantharaman & Swee Han, 2001). This study indicated significant results regarding data capturing and transmitting from ambulance to hospital EDs. It was possible to capture ambulance case records electronically more than 4 times faster than the traditional written record and 68% of data in the ambulance which is using Hospital & Emergency Ambulance Link(HEAL) while only 5% is transmissible in a non-HEAL ambulance. This study showed other benefits of using information technology (IT) in their ambulance, which are reducing the ED time of paramedics from 15 to 8 min and reducing waiting times for patient care in the ED from 35 to 17min. HEAL also worked as a decision making system by automated audit of specific aspects of ambulance workflow (Anantharaman & Swee Han, 2001). This study showed various benefits of using HEAL system in ambulances, however, the result only came from 3 ambulances in this study and it was only able to transmit data to specific hospital EDs without receiving any data from the hospital ED.

Finnell et al. conducted a study that identified current statuses of patient data exchange usage rates during a 6 month period in 2010. It shows that EMTs only used 16% of data exchange requests from all EMS 911 runs (Finnell & Overhage, 2010). It was the first HIE system between EMS ambulances and other healthcare systems and it conveys a short survey among EMT-P paramedics which showed that a majority of paramedics stated that the value of the information received was important for them in order to deliver quality care to their patients. 8 of the 58 paramedics (14%) responded that they never used the patient data request. While 24 (41%) responded that they usually or always request patient information. 38 paramedics (66%) indicated that the information from INPC was very important in helping them provide care. In this study, paramedics even said that there were significant benefits in using the HIE system to INPC among patient types, such as unconscious, uncooperative/intoxicated, and elderly patients with significant co-morbidities than other patient types. Even though HIE helped paramedics provide care to patients, HIE between ambulance and INPC has some technical problems. The majority of the problem was the connection issue between I-EMS mobile data terminals (MDT) and INPC. Since HIE in ambulance utilizes wireless technology, it caused various connection issues with real time wireless communication.

The methodology related to record linkage method, Machado et al, showed a fundamental background between deterministic and probabilistic linkage. According to Machado et al, “Record linkage is the methodology of finding a unified record from two or more records that are in different files and belong to the same entity” (Machado & Hill, 2004). In this study, record linkage methods can be deterministic or probabilistic or a combination of both. specifically, deterministic linkage is used when there is a unique identifier or if variables used for comparison are error-free and highly discriminatory, whereas probabilistic linkage takes into account the uncertainty that can exist in comparing variables used for comparison in both files. In the result of this study, the probabilistic record linkage enable the assembling of information from different data sources - births and infant deaths, 1998-birth cohort, city of São Paulo, Brazil. As a result, Machado et al. reduced the number of non-uniquely matched records and of uncertain matches, and increased the number of uniquely matched pairs from 2,249 to 2,827 in this study (Machado & Hill, 2004). This study proved that the probabilistic method is a successful tool that links and matches the data record between two different data sets.

A couple of studies show that a data matching process was successful in both deterministic and probabilistic matching algorithms in the evaluation of data matching process (Dean et al., 2001; Shaun J. Grannis, Overhage, & McDonald, 2002; Waien, 1997).

Dean et al utilized the probabilistic linkage to link the 24,299 ambulance events to inpatient hospital discharges. This was a better result than the exact linkage result of 14,621. The probabilistic linkage increased the matching results with a high matching rate and Dean et all expected that this result would expand to more patient matching processes among other departments in its hospital (Dean et al., 2001). Another study shows the positive result of using probabilistic method to link different databases. Waien conducted a study to evaluate probabilistic matching for linking a cohort of cardiac arrest (CA) patients identified in the Metro Toronto Ambulance (MTA) database in Toronto, Ontario, Canada, to their appropriate record in either the Vital Statistics Information System (VSIS) or the Canadian Institute of Health Information (CIHI) databases. In the result, a cohort of 7,079 CA patients was identified from the MTA database; 6,448 (91%) patients were accurately linked to records in 1 of the 2 outcome databases (CIHI, VSIS). This study shows that probabilistic matching algorithms showed successful results of linking two different pre-existing data sets (Waien, 1997).

Thornton et al, however, found that pre-processing a data set, such as eliminating redundant and duplicated data in data sets are a key factor to reduce matching process errors in using probabilistic matching algorithms in Intermountain Health Care (IHC) by managing the creation of duplicate patient records through a probabilistic matching algorithm. As a result, the rate of duplicate creation was cut 30% in the first 6 months in the hospital information systems (Thornton & Hood, 2005).

As mentioned in the background, Anantharaman et al showed that utilizing EMR systems in an ambulance resulted in a quantitative result. It was possible to capture a complete ambulance case record electronically at a mean time of 94 s vs. 7 min 7 s over the traditional written record. An EMR system is about four times faster than a paper-based record system. In addition, EMTs' time in the ED decreased from 15 to 8 min; the waiting time for critical care patients to be seen at the ED decreased 48% from 35 to 17 min if brought by ambulances which used the data exchange system. Even an EMR system was able to effectively prompt paramedics in performing critical treatment in close to 100% of instances (Anantharaman & Swee Han, 2001).

Deficiencies in past study

In literature review, there are only four studies conducted with EMS (Anantharaman & Swee Han, 2001; Finnell & Overhage, 2010; Mears et al., 2010; Waien, 1997). However, only two studies showed the link of informatics between ambulance and hospital information systems.

Anantharaman et al, reviewed the data link between the hospital ED and it's limited-number of ambulances which had the same EMR system with the ED while Finnell et al, showed an independent EMR system in ambulances enabling patient information exchange between all I-EMS ambulances and INPC.

The study performed in 2010 found the data request rate between INPC and I-EMS, Finnell et al, Emergency medical services: the frontier in health information exchange (Finnell & Overhage, 2010). The initial finding was 16% of data requests performed from all 911 calls to EMS over a 6 month period. However, this study only showed the result of using a patient data request rate for INPC abstract from I-EMS to INPC. No further research for analyzing the request results with success or failure was conducted. This study also did not show the success and failure rate among data requests and factors that contribute to the success and failure.

Research questions

(1) What is current usage of patient data matching requests between INPC and I-EMS ambulances? (2) What is the failure rate of data matching processes? and (3) What is the major factor for causing matching failure in the current patient identification process?

CHAPTER THREE: METHODOLOGY

Upon the approval of this study from the Indiana University Institutional Review Board (IRB), this study started with a review of Finnell et al (Finnell & Overhage, 2010). As a brief summary from the previous work, authorized EMS personnel may request patient information from the INPC through the Mobile Data Terminal (MDT) (figure 1) when they collect patient information from patients or care providers including demographic and medical information during EMTs initial assessment. This MDT has touch screen user interface and hardware keyboard input like laptops which are customized to EMT's workflow. EMTs can record all medical events with this tablet computer and EMR system during their service as well as demographic information of patients.

Figure 1 Mobile Data Terminal

Mobile Data Terminal (MDT) provides a modified look up screen (figure 2) in the electronic prehospital care report (ePCR) system to find patient previous medical record either from I-EMS server or from INPC. In order to submit the request to INPC through patient identification process, EMT uses patient lookup menu. six primary pieces of information must be present at the time of submission: (1) patient's first name, (2) patient's last name, (3) Date of Birth (DOB), (4) Gender, (5) patient's Social Security Number (SSN) and (6) patient's ZIP code of current residence; The patient identification process uses these six inputs as an identifier. The EMS personnel are messaged as to the results of the lookup request. The patient lookup page automatically loads the necessary data - six identifiers from patient information which EMTs collected during initial assessment including demographic information. Possible responses include: (1) Patient match, (2) too many patients match submitted information, and (3) no patients match to the submitted data.

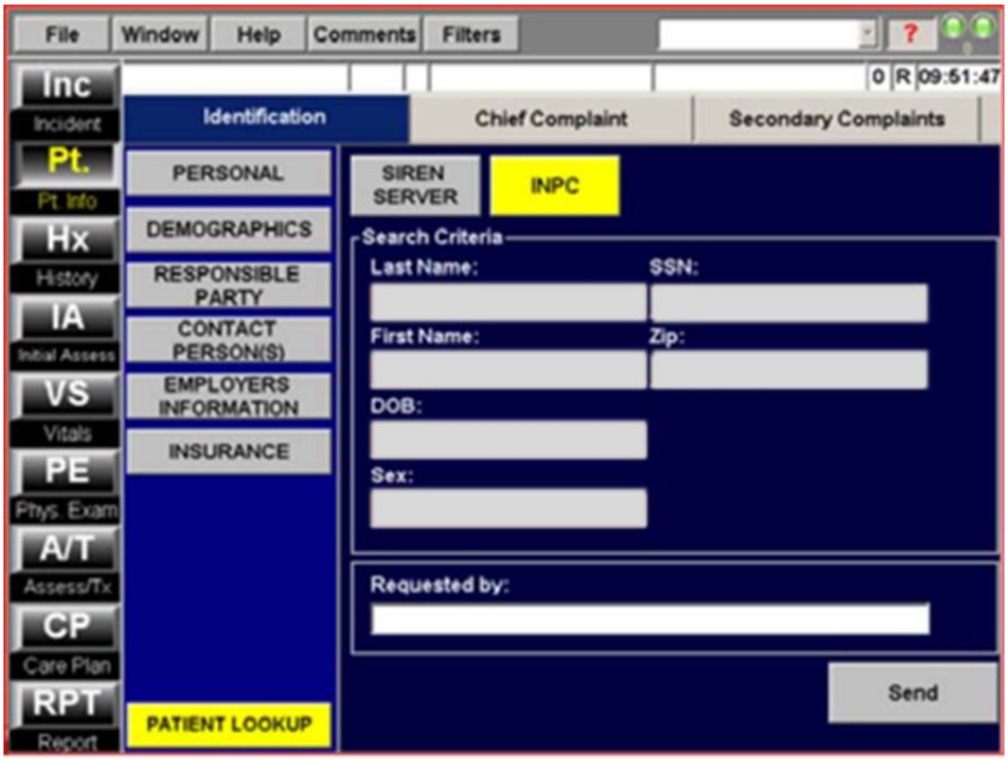

Figure 2 Mobile Data Terminal with ePCR & Patient Lookup page (Medusa Medical Technologies Inc, 2009)

This study used the 12 basic data entities to find matching rates between INPC and I-EMS since there are more fields in the data sets. In order to compare two data sets between I-EMS and INPC, initial data will be limited with the patient information, which transferred to Wishard

Hospital ED. In addition, we used the text processing scripting languages; PERL and Python (Appendix A) for matching the patient information between data sets.

Data element	Values	Data set
First Name	Alphabetic	INPC/I-EMS/Wishard Hospital
Last Name	Alphabetic	INPC/I-EMS/Wishard Hospital
Zip Code	Numeric	INPC/I-EMS/Wishard Hospital
Gender/Sex	Alphabetic	INPC/I-EMS/Wishard Hospital
Date of Birth	Alphanumeric	INPC/I-EMS/Wishard Hospital
Social Security Number	Numeric	INPC/I-EMS/Wishard Hospital
EMT ID	Alphanumeric	I-EMS
Incident No.	Alphanumeric	INPC/I-EMS/Wishard Hospital
General ID	Alphanumeric	INPC/I-EMS/Wishard Hospital
Transport Location	Alphabetic	I-EMS
Date	Alphanumeric	INPC/I-EMS/Wishard Hospital
Time	Alphanumeric	INPC/I-EMS/Wishard Hospital

Table 1 12 Data entities list

Data Collection

In this study, three sets of clinical data are required; (1) I-EMS patients transported log via EMS run, (2) I-EMS data log for the INPC abstract request for the same time line with data set, and (3) the INPC registration log for Wishard hospital ED. First, I-EMS patients transported log data resides as a web-based reporting service and it contains the EMS data that is collected through the Siren ePCR system. The I-EMS log contains a list of all patients transported during the one-year study period from July 1st, 2010 through June 30th, 2011. Second, the I-EMS data log for the INPC abstract request resides within Regenstrief Institute and contains information of the request packet sent from the EMT's MDTs. It records: (1) EMS personnel demographics: EMT's name, unit number, and service. This information, used for authentication, will use patient identification process though MDT. If EMTs are not authorized to use the process, INPC will not send out the result of the patient identification process to the EMTs who requested the INPC abstract; (2) Patient demographic data: patient's name, DOB, ZIP code, and social security number, and (3) Result of request for information: success or fail; if failed, the reason for failure: Too many patients or No patient. The INPC registration log contains all of the patient's demographic information as they were registered at Wishard hospital. This information is used to match the patient across the INPC. In this study, this data set is used as the "gold standard" to determine what the EMS personnel should have been provided when requesting patient information in order to get correct INPC abstract.

Current technology

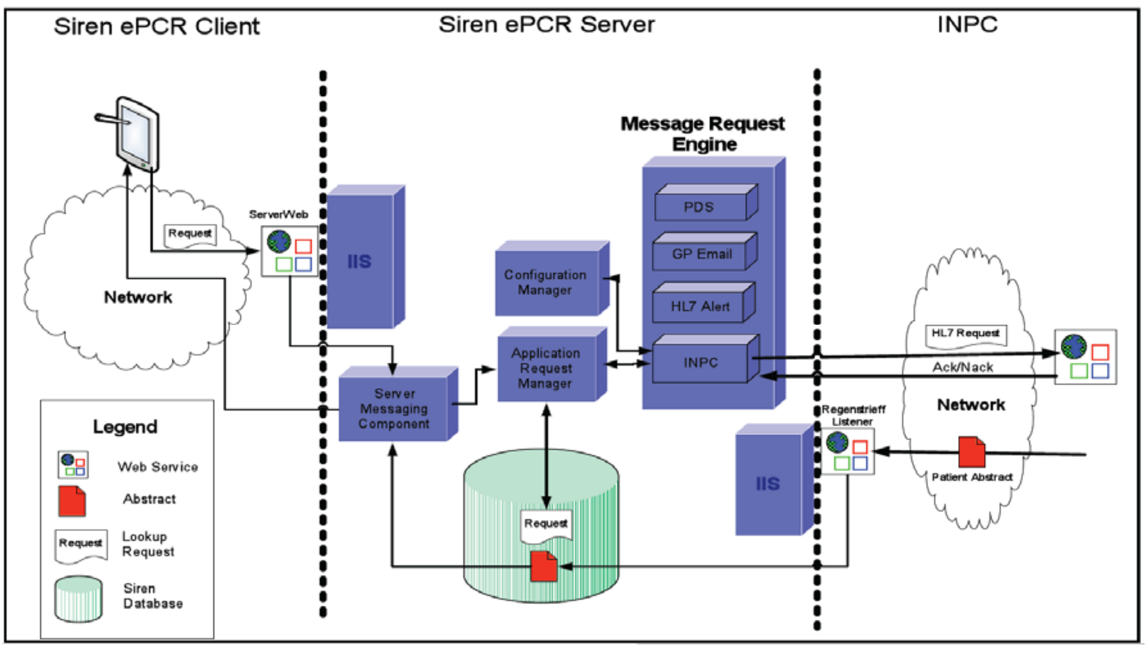

Figure 3 Patient Matching Process between I-EMS & INPC

The patient identification algorithm works as follows: (1) it first does a SSN lookup if it is present, and if only one patient found then indicate a match. (2) If no SSN provided, or not a unique match, then use the patient's name, DOB, and gender (S. J. Grannis, Overhage, & McDonald, 2004; Sideli & Friedman, 1991). If there is no match found in the INPC data, then no match result is returned. If there is more than one patient matching these criteria then ZIP code is used to narrow the search. (3) The ZIP code match tries to match on what was entered and if this fails, then the process narrows down to search with the first five digits of the ZIP code. If there is still no match, INPC sends out a result of no match to MDT.

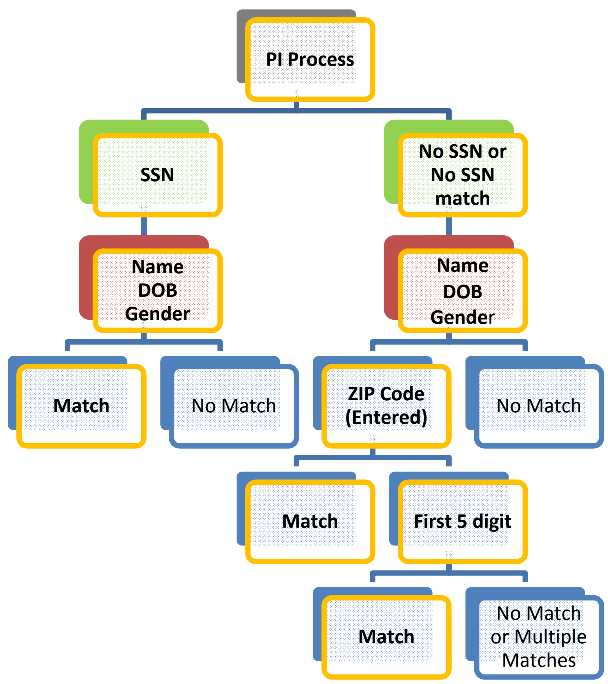

Figure 4 Patient Matching Process Algorithm

We first narrowed the I-EMS patients transported log to only those patients transported to Wishard hospital ED since the INPC has so large data sets for this study period as well as we can have direct access to log data between Wishard hospital ED and INPC. Utilizing computer programming script, PERL, we loaded this file into a Postgres database. For each EMS response, there is a unique number created and assigned to that EMS transport, known as the incident number. The I-EMS log, patients transport log and the I-EMS request for patient data log both contain the incident number. This incident number is used as the primary key to analyze data sets between I-EMS log and INPC request log; then we combined the first two data sets. This created a single data table with both the transporting agency information as well as the information provided in the request to the INPC for patient data. We then used a simple SQL query to pull the records from the database that resulted in a No Match response. These records were then manually compared to the INPC registration log to determine the cause of the failure.

CHAPTER FOUR: RESULTS

Current usage

Of the 21,215 EMS transports to Wishard hospital ED during the one-year study period from July 1, 2010 to June 30, 2011, there were 3,021 (14%) requests for INPC data out of 21,215 EMS runs to Wishard ED.

Category	Run
Test	5
ATS – Non EMS Transfer	455
AST – Non EMS Transfer	2
Total EMS Run	**21215**
Total Run	21677

Table 2 I-EMS runs to Wishard Hospital Emergency Department

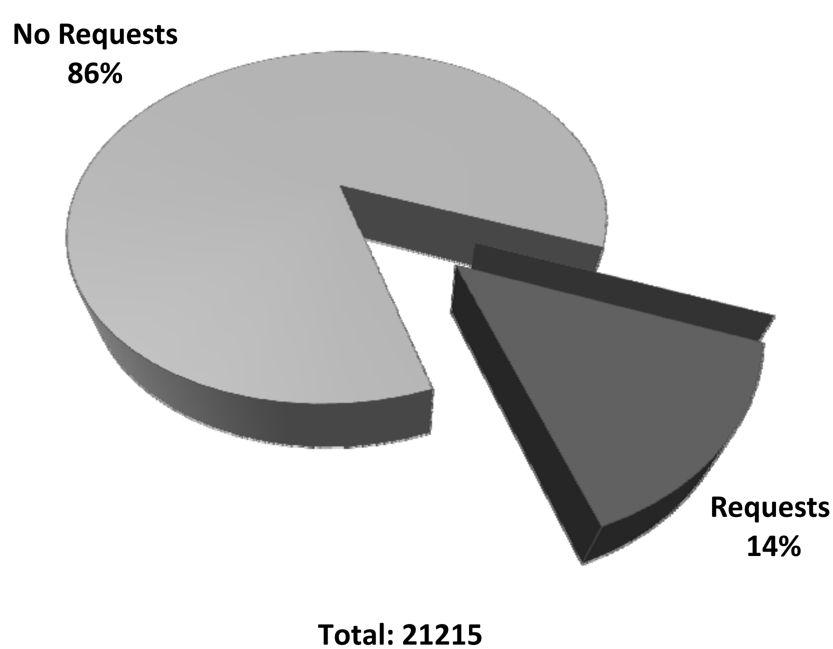

Figure 5 Analysis of Current Usage

Analysis of INPC abstract request

Regarding the 3,021 requests for INPC data: (1) we excluded 1,105 (37%) which were "Not Authorized" to retrieve the data because EMS personnel must be authorized by I-EMS in order to use patient the match process to get the INPC abstract. Therefore, there was no attempt to match the submitted data. (2) There were 1,398 (46%) requests which resulted in a unique match, (3) seven (0.2%) resulted in "unknown" error, leaving 511 (17%) which resulted in no match.

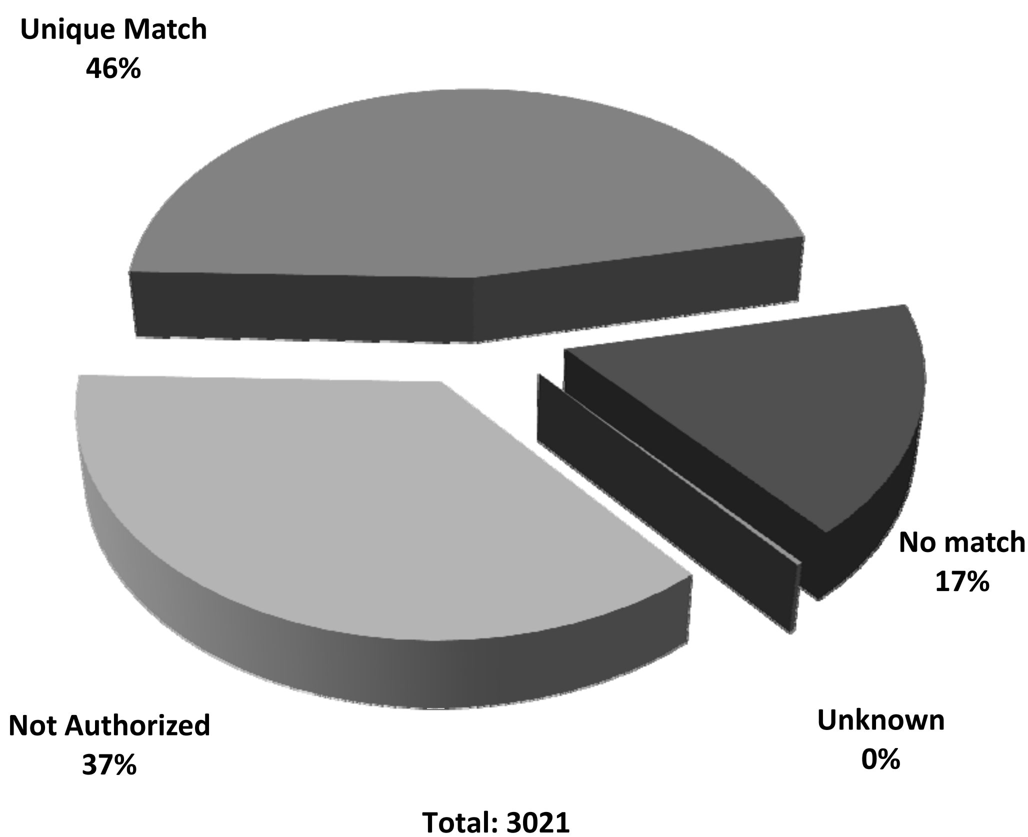

Figure 6 Analysis of INPC abstract request

Analysis of No match

Regarding the results of the 511 “no match” patients, we determined which identifiers resulted in the highest number of errors. There were 275 (53.8%) no matches due to ZIP code, 106 (20.7%) due to an error regarding the patient’s name, 59 (11.5%) with incorrect DOB, 49 (9.6%) unknown, and 22 (4.3%) had errors related to SSN.

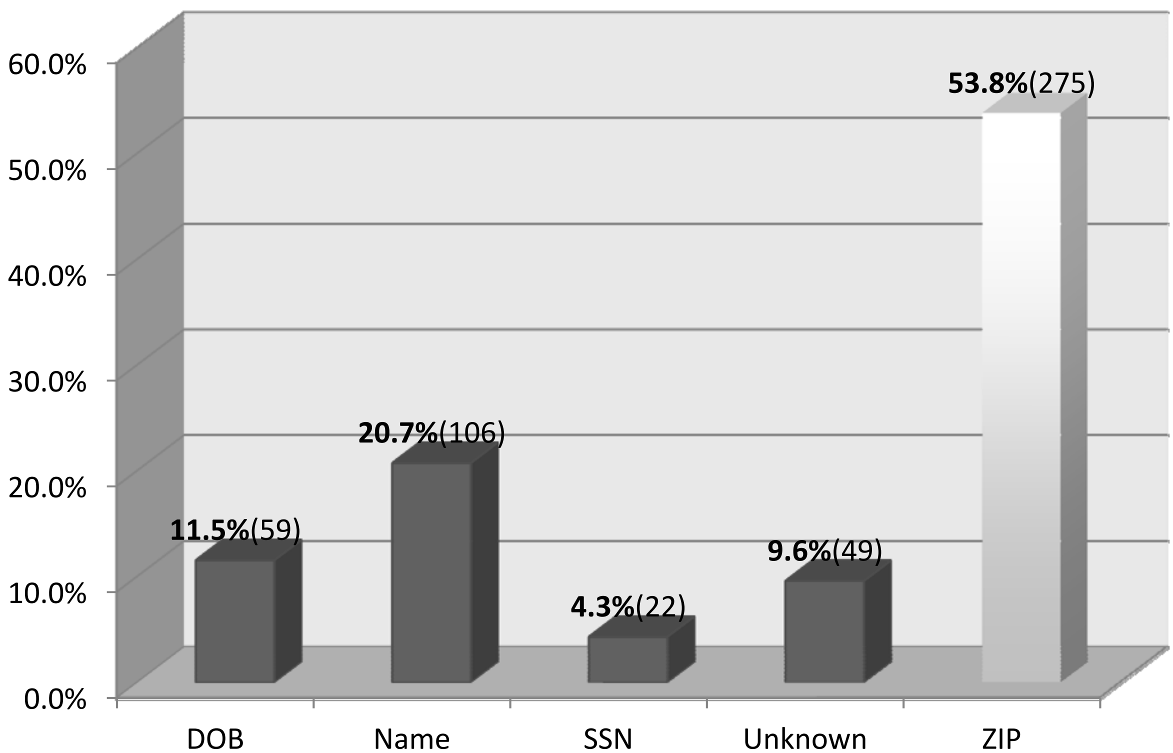

Figure 7 Analysis of No match

Analysis of ZIP code within No match result

Further analysis of the ZIP code showed a major cause of No match result was found even though the matching process used ZIP+4 code; 9 digit at the first attempt and then used ZIP code;

5 digit at the second attempt, the matching process resulted in only first three digits in ZIP code with 97.5%. This means the rest of the 6 digits are not used for patient matching process.

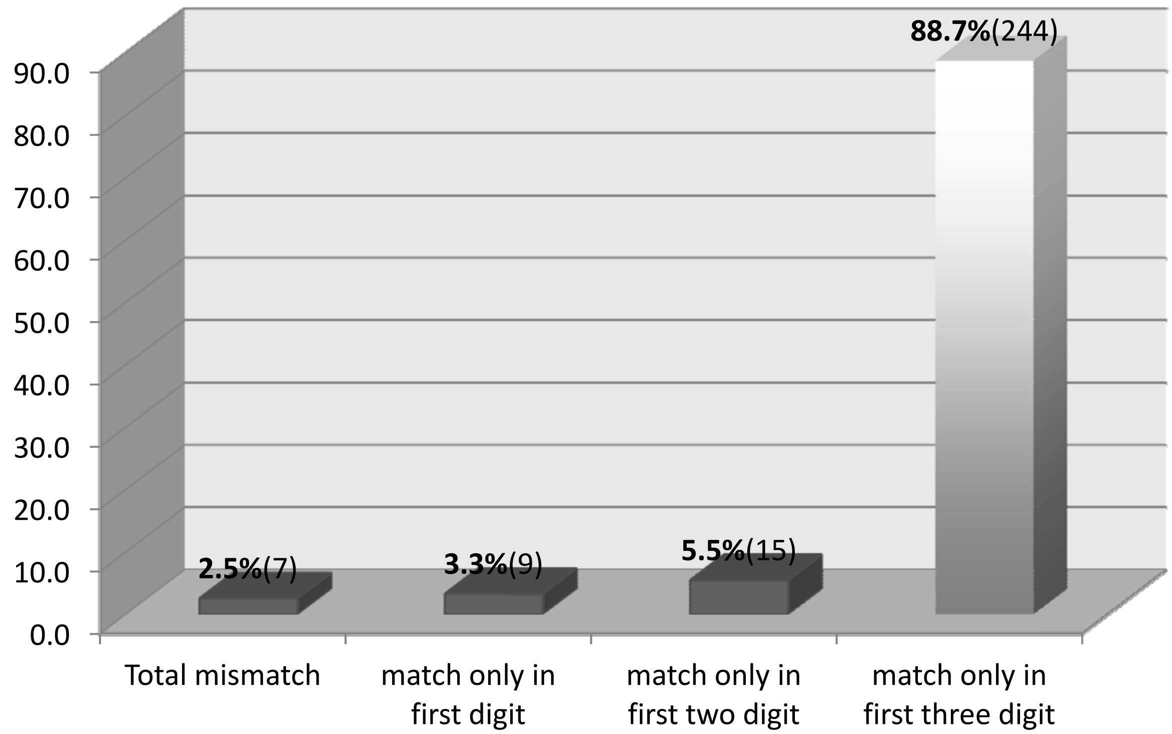

Figure 8 Analysis of ZIP code within No match result

Analysis of Name within No match result

Among the Name mismatch, there were 46 errors in patients' first names and 60 errors in the last names. There were 7 simple data input errors, mis-inputting the first name and last name, for example: inputting Smith John instead of John Smith.

Last Name in INPC	Last name from EMS input	First Name in INPC	First name from EMS input
- - - - - - - - - - - -	- - - - - - - - - - - -	Lillie	Lilly
- - - - - - - - - - - -	- - - - - - - - - - - -	Christopheer	Christopher
- - - - - - - - - - - -	- - - - - - - - - - - -	Augustine Marie	Marie
- - - - - - - - - - - -	- - - - - - - - - - - -	Dianne	Diane
Johnson	Johnston	- - - - - - - - - - - -	- - - - - - - - - - - -
Ehrgott	Hergott	- - - - - - - - - - - -	- - - - - - - - - - - -
Henley	Henry	- - - - - - - - - - - -	- - - - - - - - - - - -
Abrams	Avrams	- - - - - - - - - - - -	- - - - - - - - - - - -
Park	Seong	Seong	Park
Dows	John	John	Dows

Table 3 Examples of Name error in First name and Last name

Analysis of unknown within No match result

Of the 49 “unknown” errors in No match result, we found the information transmitted by I-EMS consistent with the information sent from the hospital system. One possibility is there was a technical issue with the matching algorithm for the non-match. Another possibility could be they were a new patient to the database through INPC. This will be discussed in the discussion session.

CHAPTER FIVE: DISCUSSION

Administrative error

In this descriptive study, we found EMS personnel requested patient data on 14% of all transports, with a “success” - Unique match rate of 46%, and a match “failure” – No match rate of 17%. The analysis of No match result found that the three major factors for causing match “failure” were ZIP code (55%), Patient Name (22%), and Date of Birth (12%).

Among the 14% of requests, 1,035 (37%) requests resulted in “No match” because EMTs who requested the INPC abstract through MDT were not authorized to use the system at the time of the request. Even though it is not guaranteed that those 1,035 cases would have resulted in a “success” in patient matching process, it would increase the unique match rate throughout the data collection period and even helped EMTs provide better health service to patients. This administrative error can be updated quickly and can greatly improve the result of the matching process.

The INPC abstract request rate was 14% and it’s lower than the result of the 2010 study which was 16% (Finnell & Overhage, 2010). However, there is a difference between the 2010 study and this study. In 2010, the data included all EMS transfers to any hospital ED which was collaborating with INPC, whereas in this study, it was limited to Wishard hospital ED. In addition to data difference of range, the 2010 study collected data for 6 months versus a one year data collection period in this study. These two different study conditions may cause this low usage rate in the matching process. This indicates that further research needs to be expanded to the entirety of EMS transfers to any hospital ED within a certain period.

Name error

Regarding the patient's name errors, we found 106 (20.7%) problems of misspelling of first and last names including seven records which switched the first and last names as part of the medical record as shown in Table 3. According to EMTs, it was possible that patients would not have any ID or documents which had their name and EMTs did not confirm the spelling of names or patients were unable to provide correct information due to their mental and physiological status due to their current illness in the ambulance. In order to reduce these user errors, EMTs need to confirm patients' names with correct spelling to avoid name error, especially for a patient whose names have many different popular spellings such as Sara versus Sarah, or Shawn versus Sean, etc.

For a technical suggestion, matching algorithms need to handle the middle name properly. If the middle name is present in INPC data and there is no middle name submitted from the EMTs, the matching process should limit the use of the name to only first name and last name in INPC data or EMTs' input to match the patient. In addition, it would be possible to provide more sophisticated logic to account for these and other common errors. Further detailed analysis will help to inform us of other algorithms that could provide a more robust match with name.

ZIP code error

The highest percentage (54%) of the errors was due to the patient's ZIP code. Looking at the data more in-depth, there were 244 (88.7%) records that matched only the first three digits, 15 (5.5%) records that matched only the first two digits, 9 records that matched only the first digit, and 7 records having a totally different ZIP code. Our PI algorithm first utilizes all of the ZIP code data (up to ZIP+4), and found ZIP code mismatch occurs within the first five digits in 97% cases.

One explanation for these findings is the dynamic nature of a patient's ZIP code. A patient's home ZIP code may change, or can be confused with the ZIP code information at the scene of an incident. We also found at least three situations with no match in ZIP code and determined these locations were homeless shelters and nursing homes within Indianapolis, suggesting the patient's home address and current residence may differ.

All "unique match" result data was reviewed manually as a delimited raw data and found there was no mismatched records within 1,398 unique match results, indicating INPC did not send out wrong patient information as a result of patient identification process.

INPC and I-EMS are the first organizations using a state wide health information exchange within the nation (Finnell & Overhage, 2010). While there are a few studies regarding EMR in EMS, this research focuses upon expanding the existing hospital based EMR system into their ambulances as a departmental implementation.

Limitations

This study was retrospective cohort study and only contained data from single institution; Wishard hospital ED and patients were transported to Wishard Emergency Department. It is possible that data from other institutions may yield different results. However, the results contained within this institution are informative and likely to aid other institutions as well. Second, due to the scope of this study, further analysis of current patient matching algorithms in INPC were not performed; however, suggestions are made to improve current algorithms for managing ZIP code data.

CHAPTER SIX: CONCLUSION

Over the past two years, the overall utilization rate of patient match processes remains stable: 16% in 2010 and 14% 2012. We believe in order to increase the utilization of the valuable data contained within the INPC, all stake holders need to be encouraged to use this system and provide more feedback. In I-EMS, administrative work needs to be done on a regular basis in order to prevent unauthorized usage of the patient matching process and on-going education for proper use of MDT including requesting the INPC abstract should be delivered to EMTs even if EMTs know how to use the system. This will improve mistyping of names; first and last names. The major factor of matching failure was ZIP code and the matching algorithm needs to be modified based on the findings in which only 3 digits out of 9 digits have been used for patient matching processes.

This study demonstrates that ZIP code is not a robust identifier in the patient identification process due to the nature of change in patient's ZIP code. In addition, it has been suggested that the patient identification process needs to find new identifiers because non-ZIP code identifiers may be a better choice due to inaccuracies and changes of the ZIP code in a patient's record.

Future Study

Future studies may be more focused on patient matching algorithms in INPC based on I-EMS input data from EMTs as well as adding new identifiers in the algorithm. These new identifiers should not be subject to change like names or gender. These could be biometric information from patients such as fingerprints, retinal identification, palm vein, etc., along with privacy protection measures.

Regarding data collection of a new study, it would need to be expanded to entire data sets from INPC affiliated hospital emergency departments with I-EMS transportation records within 3 to 6 months of a limited period of data collection due to the size of data sets.

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APPENDICES

Appendix A: Data Analysis Scripts - PERL script - courtesy of John T. Finnell.

```
#!/usr/bin/perl

# # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # #
#
#
#
#         To take | delimited file and upload to database
#
#
#
# # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # # #

use DBI;

open (IN, '< ems-req-data.txt') or die "Not able to read from file\n";
$dbh = DBI->connect( "dbi:Pg:dbname=wizerd","jtfinnell","") or print("Can't connect to
database");

@inFile = <IN>;

foreach $item (@inFile) {

        @line = split (/\|/, $item);

        foreach (@line) {       #clean up text
                        s/^\s+//;
                        s/\s+$//;
                        s/\'//gsi;
        }# end foreach

                (
                        my $id,
                        my $msgtime,
                        my $org,
                        my $shift,
                        my $station,
                        my $unit,
```

```
                    my $vehicle,
                    my $type,
                    my $service,
                    my $incident,
                    my $ein,
                    my $crew,
                    my $crewLname,
                    my $crewFname,
                    my $crewvalid,
                    my $patientLname,
                    my $patientFname,
                    my $patientMname,
                    my $dob,
                    my $gender,
                    my $zip,
                    my $ssn,
                    my $match,
                    my $pdfseconds,
                    my $pdftime,

                ) = @line;

        print "$incident \n";

        $sth = $dbh->prepare("select id from emspark where incidnum = \'$incident\';");
        $sth->execute;

        if ($sth->rows ==0) (print "No Results\n" ;}
        else {
                $res= $sth->fetchrow_array;
                $sth2 = $dbh->prepare("UPDATE emspark set emsreqlname = '$patientLname',
emsreqfname = '$patientFname', emsreqdob = '$dob', emsreqzip = '$zip', emsreqssn = '$ssn',
emsmatch = '$match', emsvalid = '$crewvalid' where id='$res';");
                $sth2->execute;

        }
}

close (IN);
$dbh->disconnect;
```

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