

Measuring the Speed and Efficacy of Clinical Decision-Making When
Comparing Two Different Data Visualizations for Medications

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WHEN COMPARING TWO DIFFERENT DATA VISUALIZATIONS

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TABLE OF CONTENTS

ACKNOWLEDGEMENTS	ii
LIST OF TABLES	vi
LIST OF FIGURES	vii
ABSTRACT	viii
CHAPTER 1: BACKGROUND OF THE STUDY	1
Introduction.....	1
Statement of the Problem.....	2
Purposes and Hypotheses	2
Limitations.....	3
Benefits.....	4
Definitions of Terms	4
Organization of the Study.....	6
CHAPTER 2: LITERATURE REVIEW	7
Introduction.....	7
Eligibility Criteria.....	8
Search Strategy.....	9
Results	10
<i>Characteristics of the Studies.....</i>	<i>10</i>
<i>Target Areas for Visual Analytics</i>	<i>14</i>
<i>Approaches to Visual Analytics</i>	<i>14</i>
<i>Comparing Different Visualizations</i>	<i>16</i>
Summary and Conclusion	18
CHAPTER 3: RESEARCH DESIGN AND METHODS	20
Study Design	20
Pilot Interview	22

Sampling	22
Measurement Procedures	23
Informed Consent.....	23
Data Collection	23
Development of Questions.....	24
Development of Visualizations	26
Experiment Environment.....	27
Organizational Setting	28
Demographic and Satisfaction Survey	28
Data Analysis	29
Limitations	29
CHAPTER 4: PRESENTATION AND ANALYSIS OF DATA	31
Introduction.....	31
Disqualified Observations.....	31
Characteristics of Participants	32
Distribution of Treatment versus Control Visualization	33
Block Responses	33
Normalization of the Continuous Variable	34
Normalization of the Binary Variable	36
Modeling the Continuous (Time) Variable	36
<i>Determining the Final Model for Time</i>	36
<i>Final Model for Interpreting Time Results</i>	37
Modeling the Binary (Response) Variable	38
<i>Determining Final Model of Response</i>	38
<i>Final Model for Interpreting Response Results</i>	38
CHAPTER 5: SUMMARY, DISCUSSION, AND IMPLICATION OF FINDINGS	40
Introduction.....	40

Findings	40
Limitations	41
Conclusion	42
Implications	42
Future Research.....	43
Summary	44
APPENDIX A: Survey Questionnaire	45
APPENDIX B: IRB Exempt Approval Letter	61
APPENDIX C: Approved Recruitment Emails	62
Initial Email	62
Follow-up Email	63
BIBLIOGRAPHY.....	65
VITA.....	71

LIST OF TABLES

Table 1: Articles Used for Qualitative Synthesis of Relevant Literature.	11
Table 2: Demographics of 23 Survey Participants.....	32
Table 3: Count of Total Observations, Treatment Observations, and Control Observations in Aggregate and for Each Block.....	33
Table 4: Population Size, Mean Task Time, and Percentage of Correct Responses for Control and Treatment Participants across Blocks.....	34
Table 5: Output of Linear Regression Model with Random Intercept Term for Individual.....	38
Table 6: Output of Logistic Regression Model with Random Intercept Term for Individual.....	39

LIST OF FIGURES

Figure 1: Flow Diagram to Yield Final Articles Included in This Review.	10
Figure 2: Survey Tree	21
Figure 3: Histogram of Residuals from Model Fit on Non-Transformed Time Variable	35
Figure 4: Histogram of Residuals from Model Fit on Natural Log Transformed Time Variable	36

ABSTRACT

Background: The percentage of patients with polypharmacy needs is increasing among a growing patient population. As a result, the amount of time health care professionals require to make clinical decisions based on current and past medications is increasing. Health care professionals need methods for increasing the speed of clinical decision making without sacrificing the quality of care. The goal of this study is to demonstrate how modifying the data visualization for patient medication histories will change decision making speed or efficacy.

Methods: We compared two groups across five randomized blocks. Group 1 responded to questions based on the control data visualizations derived from an existing electronic health record. Group 2 responded to questions based on the experimental data visualization based on a medication history developed by a team led by Dr. Jeffrey Belden. All medical information presented to both groups is identical.

Each block represents a core clinical task associated with leveraging the medication history for a clinical decision extrapolated from anecdotal scenarios in primary care. Block 1 asks the participant to identify current prescriptions. Block 2 asks the participant to identify past prescriptions. Block 3 asks the participant to identify the length of time a patient has been prescribed a specific drug. Block 4 asks the participant to identify all new prescriptions in a given time interval. Block 5 asks the participant to identify a dosage change for any prescription in a given time interval.

Each block holds two questions, identical in wording, differing only on the visualization presented to the participant. The survey is configured to randomly present one question from each block to each participant. Regardless of the question presented, we additionally track the response time for each block measured as the last click on the survey page before the “submit” or “next” button is clicked. Participants are shown only one question per page to increase the relevance of time tracking.

Results: Twenty-three participants enrolled in the study. A total of 112 observations were collected across five randomized blocks. The average task time for control was 1366.3+/-10.35 and the average response time for treatment 1773.23+/-10.4; however, the T-value was -1.313, thus the results were not statistically significant. The average task correctness for control was 30.61% and the average task correctness for treatment was 66.67% with a p-value of 0.000502.

Conclusions: Task correctness saw a significant increase in the probability for a correct response when using the treatment visualization versus the control visualization. Additional research is required to determine the effect of the treatment visualization on task time. The findings may have a significant impact on how medication histories are presented to care provided through the electronic health record.

CHAPTER 1: BACKGROUND OF THE STUDY

Introduction

Electronic Health Records (EHRs) have grown in functionality and availability over the past two decades.^[1-3] The American Recovery and Reinvestment Act of 2009 mandates all private and public health care providers must adopt and demonstrate “meaningful use” of an electronic health record in order to maintain Medicaid and Medicare reimbursement levels by January 1, 2014.^[4]

As the EHR becomes ubiquitous in health care, the role of time and time-oriented data increase in importance.^[5] The rapid change in our ability to store, extract, and analyze data is a direct result of our evolving information infrastructure.^[6] For example, the continuous generation of large, diverse, complex, and/or longitudinal datasets (i.e. handwritten notes, flow sheets, forms, printouts, lab-slips, orders, journal reprints, and an occasional identification tag) from a variety of instruments, sensors, and/or computer-based transactions requires methods for human interaction to improve at the same rate these datasets are generated.^[6, 7] Time constraints and high demand for information create cognitive load on physicians.^[8] The given environment, combined with an increasing high frequency of polypharmacy patients, lead to mismanagement and medication errors.^[9-11]

Statement of the Problem

In a 2011 study, the annual cost of measurable medical errors reached nearly \$17.1 billion.^[12] Misuse, overuse, and underuse of medications are a large majority of measurable medical errors.^[12] Anticipated benefits with an EHR remain unproven.^[13] Instead, an EHR accentuates workflow and cognitive challenges when introducing new technology.^[14-16] Recent research offers visualization techniques for retrieved data, but none have offered a comparative methodology for evaluating efficacy and accuracy of clinical decision-making.^[13, 17, 18] Modifying the visual representation of the EHR information may provide greater insight to improve the management of polypharmacy patients.^[19]

Purposes and Hypotheses

The increase in comorbid patients and lack of dynamic patient care tools have resulted in a high frequency of medication errors for polypharmacy patients in primary care.^[20] The demand for tools and methods to address this issue is at an all-time high. We hypothesize a statistically significant change in the speed and efficacy of clinical decision-making will result after modifying only the visual representation of the medication history. A resident or attending physician in primary care will increase the speed and accuracy for medication related questions based on information provided in one of two medication histories: Control medication history and the Med Treatment medication history.

Limitations

Several limitations present when using the survey mechanism for the speed and accuracy of clinical responses. Limitations are recognized below.

1. Participation in the trial is voluntary and limited to providers who have access to email, a computer, internet access, and a compatible web browser. Data collection inadvertently excludes some information belonging to those not enrolled.
2. The survey questions are designed for a participant to find information within a given visualization. The size of text, size of computer screen, and visual acuity of the participant may have limited a participant's response performance.
3. The visualizations were not interactive. Responses for control participants may have changed if participants could have manipulated the presentation of information.
4. The survey did not account for any bias for the control. All participants use the control visualization to some extent in their professional workday. Responses to the survey may change if participants had never seen the control prior to the survey.
5. The survey did not account for any bias in the treatment. As the treatment visualization is publically accessible on the internet, participants could have learned of the treatment prior to the survey. Additionally, learning on the treatment visualization could have affected responses as participants

progressed between questions assuming they were randomly shown the treatment visualization more than once during the survey.

Benefits

Several benefits present when using the survey mechanism for the speed and accuracy of clinical responses. Benefits are recognized below.

1. The study demonstrated optimizing the visual analytics for patients' medication history increases the accuracy of common clinical questions without changing the response time.
2. The study suggests more complex data collection or changes to the data architecture are not the only response to improving EHR benefits.
3. The study demonstrates presenting information to match the intended function produces a measurable benefit to patient care.
4. The study provides findings to inform studies with larger populations or more complex scenarios.

Definitions of Terms

Clinical Decision Making – The process by which we determine who needs what, when.^[21]

Cognitive Load – The total amount of mental effort used in working memory and classified in three categories: intrinsic, extraneous, and germane.^[22, 23]

Dashboard – A visual display of the most important information needed to achieve one or more objectives; consolidated and arranged on a single screen so the information can be monitored at a glance.^[24]

Data Visualization – A synonymous term for visual analytics.^[25]

Electronic Health Record (EHR) – “The Electronic Health Record (EHR) is a longitudinal electronic record of patient health information generated by one or more encounters in any care delivery setting. Included in this information are patient demographics, progress notes, problems, medications, vital signs, past medical history, immunizations, laboratory data, and radiology reports.”^[26]

Evidence-Based Medicine (EBM) – Is the conscientious, explicit, and judicious use of current best evidence in making decisions about the care of individual patients.^[27]

Medical Error – An act of omission or commission in planning or execution that contributes or could contribute to an unintended result.^[28]

Phenome – Set of all expressed phenotypes^[29]

Polypharmacy – “The use of multiple medications.”^[30]

Task Correctness (aka. Accuracy of decision making) – The rate by which a participant provides a correct response to a task or question.^[31]

Task Time (aka. Speed of decision making) – The time measured between initiating an event and finalizing the event.^[31]

Visual Analytics – The science of analytical reasoning facilitated by advanced interactive visual interfaces.^[25]

Organization of the Study

In this study, we surveyed care providers to determine the difference in decision making when using two different medication histories. We used speed and accuracy as metrics for determining a difference. Our definition for speed of decision-making (task time) is: the time between initiating a single survey question and the last mouse click on the question (equivalent to clicking “submit”). Accuracy (task correctness) is defined as pass/fail to a given response. We captured each metric using software designed to collect participant responses.

CHAPTER 2: LITERATURE REVIEW

Introduction

The review of related literature focuses on health care related visual analytics within an electronic health record. The methods used to develop systematic review of data visualizations related to visual analytics are as follows: define eligibility criteria, translate search strategy, conduct literature searches, retrieve studies, check eligibility, and abstract outcomes.

The initial investigation for quantitatively measuring the effect of visual analysis on decision making started with evaluating the state of the art for current visualizations. Rind et al. investigates existing data visualization software based on the following criteria: (1) data types covered, (2) multivariate analysis support, (3) number of patient records used (one or multiple), and (4) user intents addressed.^[17] The 2013 study determined effective information visualization can facilitate analysis for patient treatment and clinical research.^[17] The evaluation metrics used in the Rind study, however, do not evaluate the effectiveness of information visualization at the point of care and determined more investigation is required.

To start broadly, the investigation focused on discovering studies that included “visual analysis” and “electronic health records”. The following designation attempts to group the returned articles in a meaningful category.

Eligibility Criteria

Across three library data bases, selection criteria for inclusion in the review were (a) includes the use of visual analytics and (b) study relates to electronic health records. For the second round of eligibility, titles and abstracts were screened to determine articles that would receive a full document review. After reviewing duplicates, screening criteria excluded articles based on the following:

- Non-English
- Related to nursing medication calculation skills and education
- Health care risk management
- Drug formularies
- Drug Interactions
- Psychological work environment
- Comparing datasets from websites
- Visualization of cohort analysis
- Visualization of regular expressions
- Social network analytics
- Phenome or genomic analysis
- Exploratory data mining; associational data mining
- Pathway analysis
- Geographic information systems

Final screening conducted on full text articles leveraged an approach for a similar literature review from West et al. and excluded studies that did not include a

visualization, did not include empirical findings, was a position paper, was a literature review, or discussed prototype / conceptual model.^[32]

Search Strategy

The previously mentioned eligibility criteria were translated into a search strategy for health care randomized controlled trials focusing on medication errors. To identify relevant studies, a search of the English-language literature was conducted in Ovid™, CINAHL™, and SCOPUS™ databases. The Medical Subject Heading (MeSH) term “electronic health records” was too exclusionary when combined with “visual analytics” and therefore was treated as a keyword.

The study selection process included applying selected terms to Ovid and CINAHL Databases, then combining keyword results to narrow returned articles. Eligible articles matched the following search strategy: All.Fields “electronic health records” AND All.Fields “visual analytics”.

The search for articles began with electronic databases. Applying the search strategy across all identified databases, Ovid returned 11 citations, CINAHL returned 2 citations, and SCOPUS returned 136 citations.

After applying eligibility criteria, 32 studies passed the abstract screening process and were added to the articles that received full document review. After examination, 9 articles were identified to be a part of the qualitative synthesis. The search was limited to studies included within the default database publication years.

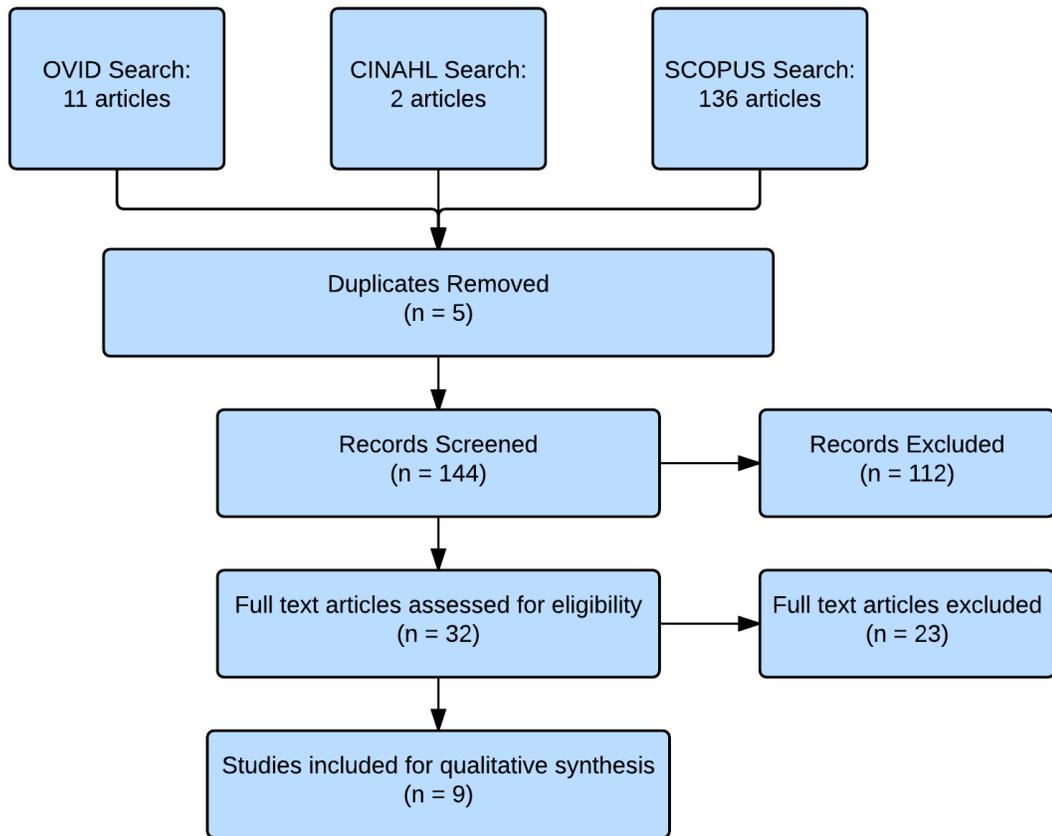


Figure 1: Flow Diagram to Yield Final Articles Included in This Review.

Results

Characteristics of the Studies

This section identifies the final set of articles included for qualitative synthesis. Table 1 summarizes 9 articles on visual analytics in electronic health records relevant to the eligibility requirements.

Table 1: Articles Used for Qualitative Synthesis of Relevant Literature.

Study	Visual Analysis	Sample Population	Aim	Measurements	Outcomes
(Aigner, 2012)	Semantic Time Zoom technique	20 student and faculty participants	Comparative evaluation of an interactive time-series visualization that combines quantitative data with qualitative abstractions. ^[31]	Task completion time and task correctness	No change in task correctness, but faster task time.
(Brown, 2014)	Visual attention patterns on electronic notes in an electronic health record.	10 Hospitalists (physicians) in a large medical center using Cerner PowerChart.	Presents temporal summaries, an interactive visualization technique that highlights the prevalence of event occurrences for the purpose of spotting trends over time and comparing several groups of records. ^[33]	Time spent reading each section of an electronic note.	Direct correlation between character count and time spent reading. Medication section received lowest percent glance rate regardless of character count.
(Cho, 2014)	Rippled graph for stroke patient records	14 participants	Proposes a unified visualization model, called a ripple graph, that takes the benefits of both of the bar graph and line graph with enhanced graphical integrity for not only the regularly measured but also irregularly measured time-series data. ^[33]	Task time, correctness, and subjective satisfaction	Ripple graph outperformed other studied visualization on task time, task correctness, and subjective satisfaction.

(Kwon, 2012)	An investigative analysis tool, called TIMEINVESTIGATOR, consisting of five cross-linked views	12 paid participants	To study the influence of temporal visualization on investigative analysis of document collections. ^[34]	Temporal event sequences for the following tasks: which view a participants interacted with, when an insight report was submitted, the individual scores for insight reports, and the number of entities visible in the tool.	Study identified three benefits for the visualization: 1) uncovers entity relationships, 2) filtering out entities, and 3) identifies patterns.
(Ledesma, 2015)	2 different visualizations: 1) Cleveland and McGill 2) hGraph	30 participants	Study how the visual representation of holistic health data affects the capability of non-medical experts to derive insights. ^[35]	Subjectively measured responses on a 5-point scale to 2 tasks. Time on task.	No conclusive outcome shared.
(Rind, 2011)	VisuExplore application	16 participants	We present a design study of an interactive visualization system, called VisuExplore, to support long-term care and medical analysis of patients with chronic diseases. VisuExplore offers interaction techniques for effective exploration of time-oriented data and employs simple, but intuitive visualization techniques. ^[18]	Qualitative responses to 4 open ended questions.	Concludes tool is successful for ease of use, interaction techniques, and variable metadata.

(Simpao, 2015)	Patient medication dashboard developed using Qlikview	Targeted inpatient providers and pharmacists. Analysis was performed on 2,391,880 medication alerts. Total pharmacists and physicians not specified.	To develop and evaluate an electronic dashboard of hospital-wide health record medication alerts for an alert fatigue reduction quality improvement project. ^[36]	Average change in ratio of alerts to order before and after implementing a medication dashboard.	Safety event rate decreased after removing irrelevant medication alerts.
(Wongsuphasawat, 2012)	Two visual tools for determine matching records.	18 graduate and senior undergraduate students.	Temporal sequence events: (1) aggregate multiple event sequences, (2) display the aggregate pathways through different event states with timing and cardinality, (3) summarize the pathways corresponding outcomes, and (4) allow users to explore external factors that correlate with specific pathway state transitions. ^[37]	Time, error rate, and subjective feedback	No significant difference in error rates with faster performance on tasks time for two of five tasks.
(Zhang, 2013)	The application of the "5 Ws" when choosing a visualization	6 physicians and 2 health informatics professionals.	Two sets of questions. The first set aimed at finding out whether our system can help physicians to quickly and accurately find information. The second set was more focused on design details along with some general questions. ^[38]	Correct Answers (accuracy); time to respond; and qualitative responses	Task time ranged from 5.6 6.5 seconds with task response at 100% accuracy. No statistical significance was identified for the results.

Target Areas for Visual Analytics

This section reviews articles identifying areas within the electronic health record where visual analytics could provide a benefit.

Brown, P. J., et al. found, on average, the “Impression and Plan” and “Medication Profile” zones showed the highest relative volumes of text with considerable variation.^[33] Specifically, the medication profile could consume as much as 50% to as little as 2% of the total medication note.^[33] The study found a direct correlation between the total electronic note character count and the length of time physicians spent reading.^[33] However, the medication section consistently received the lowest percent glance rate from all participants regardless of the amount of text in the section.^[33]

Simpao, A. F., et al. found the medication serious safety event rate decreased over the study duration after removing clinically irrelevant medication alerts.^[39] Participants used a visual analytics dashboard to monitor the frequency of triggered drug-drug interaction (DDI) alerts.^[39] After removing a DDI alert, the study evaluated six (6) longitudinal measures for both pharmacists and providers.

Approaches to Visual Analytics

This section reviews articles attempting to create a framework for determining which visualizations to use in various health information scenarios.

Zhang et al. examines the “5 Ws” (who, what, where, when, why) with respect to creating a speed, usability, and efficacy study.^[38] The study evaluated a new visualization to aid physicians when determining a patient

condition/disease.^[38] A pilot survey used a mix of (3) quantitative and (5) qualitative questions (8 total) to assess the tool's efficacy and usability.^[38] Additionally, the time for a physician to respond to a quantitative question was recorded.^[38] The average response time across the three questions ranged from 5.6 seconds to 6.5 seconds with 100% accuracy.^[38] No statistical significance was identified given the limited population.

Aigner et al. focused on evaluating a visualization method for qualitative abstractions and the associated quantitative time-oriented data, referred to as Semantic Time Zoom (STZ).^[31] The study hypothesizes the "STZ technique is effective and efficient for lookup and comparison tasks on qualitative abstractions, as well as for lookup and comparison tasks on quantitative values linked to qualitative abstractions when investigating single and multiple time-oriented variables".^[31] The study used 20 student and faculty participants that use graphical data representation in their daily routine.^[31] Participants took a questionnaire and were measured on "task completion time" and "task correctness".^[31] When compared to another technique from a separate study (KNAVE), STZ demonstrated no significant difference in error rate, but measurably outperformed KNAVE with regard to task completion time.^[31]

Kwon et. al. investigated "the influence of temporal visualization on investigative analysis of document collections".^[34] Using 12 paid participants, the study introduces "TIMEINVESTIGATOR", an investigative analysis tool consisting of five cross-linked views to analyze the document collections.^[34] The study recorded temporal sequences across four outcome areas: which view a

participant interacted with, when an insight report was submitted, the individual scores for insight reports, and the number of entities visible in the tool.^[34] The study concluded three main benefits when using the timeline view in TIMEINVESTIGATOR: 1) it is vital for uncovering important entity relations; 2) it allows for filtering out unimportant entities; and 3) it helps identify patterns that are invisible in the emergency room (ER) view.^[34]

Rind et al. conducted a usability study on a new visualization application called VisuExplore.^[40] VisuExplore presents time oriented patient data related to chronic disease using a combination of line plot, bar chart, event chart, and timeline chart.^[40] Sixteen (16) student participants responded to three (3) open-ended questions.^[40] Based on the outcomes from the qualitative analysis, the study proposes a successful tool through a combination of easy to understand and mostly well-established visualization techniques, powerful interaction techniques, and use of variable metadata.^[40]

Comparing Different Visualizations

This section identifies studies that compared two different visualizations to determine a difference in outcomes.

Wongsuphasawat et al. conducted a controlled experiment of two visual interfaces (LifeLines2 and Similan2) platforms to determine “fit” for targeted research questions.^[37] Eighteen graduate and senior undergraduate students were asked to perform five (5) tasks based on three research areas using the different visual interfaces.^[37] Participants were measured on error rates, time on

task, and presented with qualitative questions regarding their experience with the two interfaces.^[37] Results found no significant difference in error rates across any task.^[37] Performance time on task was faster with Task 1 for LifeLines, and faster on Task 5 using Similan2.^[37] Tasks 2-4 have significant overlap in the performance time with no clear outcome.^[37]

Cho et. al. proposed a unified visualization model, called a ripple graph, integrated within a large application call “Stroscope”.^[41] Stroscope is a visual analytics application designed to explore large time-series data.^[41] The ripple graph is intended to solve the issue of analyzing unevenly spaced time-series data within Stroscope.^[41] The study created a four task questionnaire to record the task time, task correctness, and subjective satisfaction between four different visualizations: line graph, bar graph, interactive horizon graph, and the ripple graph.^[41] The findings suggest the ripple graph outperformed all other visualizations across task time, task correctness, and subjective satisfaction.^[41]

Ledesma et al. created a block randomization study to compare three different visualization approaches: 1) Cleveland and McGill Framework, 2) hGraph, and 3) table of figures (control).^[35] Thirty (30) participants were evaluated on their ability to create a hypothesis for status of a simulated patient across two activities: 1) health and well-being, and 2) the risk of developing a disease.^[35] Performance on the hypothesis was based on established criteria and on the investigators’ opinion.^[35] Additionally, the study recorded the average time to present a hypothesis between each visualization.^[35] No conclusive outcome was shared.

Summary and Conclusion

This chapter reviewed related literature focused on health care related visual analytics within an electronic health record. After a systematic review of the literature, 9 articles were identified for qualitative synthesis.

Three categories were identified among the selected literature. First is determining a target area to focus improvement efforts on within an electronic health record. Medications are consistently identified.^[33, 38, 39] Based on the evidence, medication lists are often given less attention and medication alerts are ineffective in increasing awareness.^[33, 39]

The second category identifies different approaches to visualizations. The aims for the visualizations center around comparing events within the electronic health record to determine a chronic disease or issues related to chronic disease.^[31, 34, 38, 40] Time-oriented visualizations are interpreted as a key problem area where innovation is needed. Study designs included quantitative, qualitative, or a combination of both metrics to evaluate the success of a given visualization.^[31, 34, 38, 40]

The third category consists of studies that compare two different visualizations. Common metrics among these studies are task time and task correctness.^[35, 37, 41] Task time is the recorded time between when an activity/task/question is presented to the participant (initiated) and when the participant response completes. Task correctness is the binary outcome from a participant's response (i.e. the response is correct = 1, the response is incorrect

= 0). In some instances, qualitative responses were collected to measure the participant's satisfaction with using the visualization.^[37, 41]

The reviewed literature influenced the methods and hypothesis of this study in three significant ways. First, the study metrics: Our study measures performance based on task time and task correctness. Our study elected to remove the qualitative components because they were not consistent across all design approaches. Second, the study approach: Our study creates a 5-task questionnaire to compare two different visualizations similar to the Wongsuphasawat et. al. approach. Third, the focus area: We found several studies looking broadly at chronic disease and time-oriented events, but none that focused on measuring the effect of changing the visualization for the medication history. Given the correlation between polypharmacy patients and chronic condition patients, we saw this as an opportunity for innovation and investigation.

CHAPTER 3: RESEARCH DESIGN AND METHODS

This chapter addresses the research methods used in this project. A survey method was used to determine responses to information presented to providers and users, collect basic demographic information from participants, and track the time required to respond to each question. The survey was offered in an online web format using a third-party questionnaire platform. Responses were presented to respondents using a combination of radio button and check-box multiple-choice questions. Each question was presented as a randomized block. The survey tracked two main metrics: task time and task correctness.

Study Design

A purposive sampling technique was used for the purposes of this survey. A specific segment of health care providers from the departments of Family & Community Medicine (FCM) and Internal Medicine (IM) was chosen to provide relevant feedback for the two focuses of this study. The survey was designed so that personnel who work with electronic patient medication histories can provide the relevant information. Keeping this in mind questions were developed to address the nature of the project as well as the intended audience. A general process flow outline was developed as a guide for building the survey in Qualtrics (Figure 2).

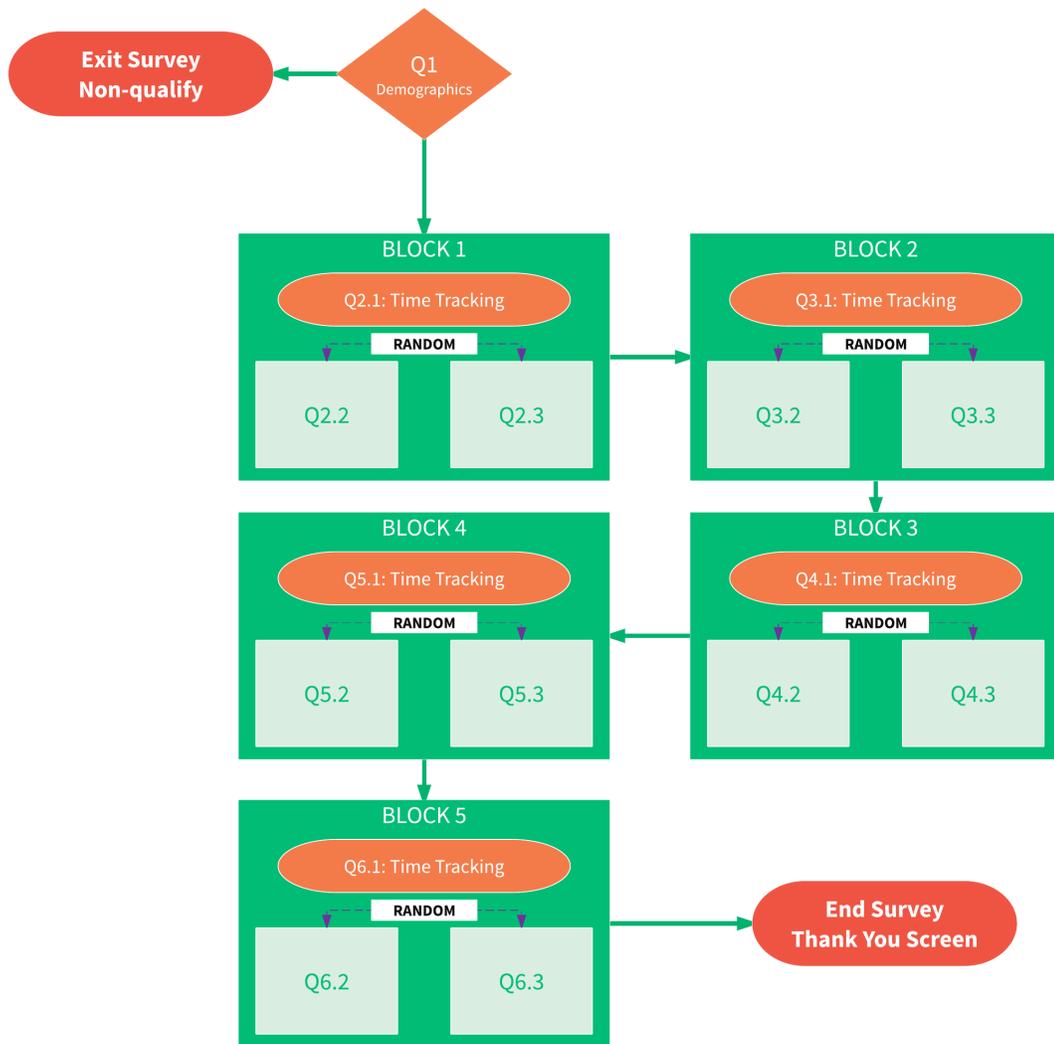


Figure 2: Survey Tree

Participants leverage a visualization (control or experiment) to respond to each question. Each clinical question had two (2) assigned visualizations and participants were randomly presented one of the two assigned visualizations. Questions pertaining to both control and experiment groups (i.e. time to respond and demographic information) were assigned to all participants.

To measure the speed and efficacy of clinical decision making when utilizing different data visualizations, data were collected using an electronic surveying tool, called Qualtrics, provided by the University of Missouri. Family Medicine and Internal Medicine resident physicians and faculty respond to five (5) questions based on core clinical activities related to a patient medication history. (APPENDIX A: Survey Questionnaire) A quantitative approach was used to determine the differences in task time and task correctness between participant groups. Groups were determined based on randomly assigned visualizations. This involved an electronic survey instrument to capture both metrics. This study is approved by the University of Missouri Health Sciences Institutional Review Board (Project Number: 2003333).

Pilot Interview

The survey was validated by two pilot FCM faculty. The purpose of piloting the survey is to identify issues and identify questions potentially misinterpreted by participants prior to presenting the final survey to participants.

Sampling

In this study, we targeted 286 total potential participants from the UMHS Department of Medicine. UMHS participants were selected for the target population because of their daily interaction with the EHR medication history and potential availability. Recruitment was based solely on an individual with an email address associated with at least one of three distribution lists containing resident

physicians, attending physicians, and nurse practitioners. We successfully recruited 23 participants for our study.

Measurement Procedures

The survey used multiple choice questions, asking participants to select the best possible answer (or answers), in an effort to allow a uniform line of answering. The resulting data were then presented in both table and chart form. Neutral exits (e.g. N/A or other) were used as options to continue the survey without answering with a standard response. Results will be presented in Chapter 4.

Informed Consent

The study was reviewed by the University of Missouri Health Sciences Institutional Review Board as an exempt project (APPENDIX B: IRB Exempt Approval Letter). A waiver of documentation of consent was included which clearly stated that participation in the study was completely voluntary and that the participant could stop the interview without consequences at any time if they no longer wish to participate in the interview (APPENDIX C: Approved Recruitment Emails).

Data Collection

Survey data were collected between September 09, 2015 and October 18, 2015. Reducing undesirable interruptions was the responsibility of participants, but not controlled for in their testing environment. The instructions on how to

complete the survey were presented electronically to participants prior to displaying any survey questions. Qualtrics recorded the initiation time, time to first click, the time to last click, time to submit, and responses for each survey question. Task time used the “time to submit”; the time between when a task was initiated and when the participant submitted a response. Task correctness was determined based on the comparison of the pre-determined response and the participant response.

Participants completed the tasks without the assistance of a facilitator. Prior to participants completing the survey questions, they completed the demographic questions. The survey concluded with a thank you page providing contact information for the principle investigator.

Development of Questions

To derive the questions for the survey, we began by collecting anecdotal scenarios physicians commonly encounter when needing to reference the medication history in the electronic health record. As each scenario carried a large assumption of medical knowledge, individual tasks were derived from each scenario. Tasks were grouped into five conceptual categories. Five total questions, one question specific to each category, were developed for the survey. Demographic questions for each participant were also developed.

Conceptual Categories Corresponding to Randomized Blocks:

1. Identifying Current Prescription on a Medication History
2. Identifying Past Prescription on a Medication History

3. Identify the Length of Time a Medication has been Prescribed
4. Identify New Prescriptions in a Given Time Interval
5. Identify a Dosage Change in a Given Time Interval

Category Survey Questions Corresponding to Randomized Blocks:

1. Based on the visualization provided, please identify which of the following is not a currently prescribed medication?
2. Based on the visualization provided, please check all past prescriptions. Our definition of "past prescriptions" includes only medication prescribed AND not currently in use.
3. Based on the visualization provided, how many years has Alendronate been prescribed to the patient?
4. Based on the visualization, select all new medications from the list below prescribed between 2012 and 2013. New medications are all medications with no record of any previous prescription to the patient.
5. Based on the visualization, identify all medications with a dosage change between 2013 and 2014.

Demographic Survey Questions for All Participants:

1. Gender
2. Age
3. Computer Skills
4. Experience with any EHR other than Cerner's PowerChart
5. Number of years as a professional health care provider.

Development of Visualizations

As with the conceptual categories and associated questions, the two data visualizations for our study were created using anecdotal scenarios physicians commonly encounter when needing to reference the medication history in the electronic health record. All data are identical across each visualization. They differ only in their presentation of the data. All medications have the same start date, end date, and dosage history. All medications are sorted by descending, alpha-numeric.

The control visualization is based on the medical history available in PowerChart, the Cerner electronic health record used at the University of Missouri Health System. The medication history in PowerChart uses a combination of graphical indicators and textual narrative auto-generated from the EHR database. Our study recreated each element of the medication history removing patient and non-essential header information. While using graphical visualization to indicate current and past medication via a textbox, the control visualization relies heavily on organized, concatenated, and grouped text.

The experimental visualization is based off the medication timeline described in InspiredEHRs.org. The experimental visualization abandons the tabular format used in PowerChart in favor of a bar graph. Text is used throughout the visualization in combination with graphical presentations for length of time, dosage amount, and year indicators. Additionally, it uses text formatting to change the color of text to distinguish between current and past

medications, plus uses bold text for medication name to help visually separate the name from additional prescription information.

Experiment Environment

In this study, the computer monitor participants used to display the Qualtrics survey was not controlled. However, we strongly recommended participants use a screen resolution no smaller than 1280x800, the common resolution for laptop workstations. All experiments were run using the participant browser of choice and required participants had access to a University Missouri Health System (UMHS) email account. All quantitative responses were collected using Qualtrics as the physicians answered basic questions using data visualization of patient medication history. No facilitator was present for any survey response.

The goals of the study and detailed methods with directions were prepared for the participants to review electronically at the start of the survey. Physicians were presented their rights as a participant that acknowledge: participation was voluntary, volunteers have the right to stop participating at any time, and although the session was recorded, volunteer privacy and personal identification were safeguarded. An email address was included in the explanation to allow participants to ask any questions they may have before or after taking the survey.

Organizational Setting

This study was conducted with participants employed at the University of Missouri Health System (UMHS), a 536-bed, tertiary care academic medical hospital located in Columbia, Missouri. The Healthcare Information and Management Systems Society (HIMSS), a not-for-profit organization that rates how hospitals are implementing electronic medical record (EMR) application, has awarded UMHS with Stage 7 of the EMR Adoption Model. UMHS, therefore, uses electronic patient charts, analyzes clinical data using data warehousing, and electronically shares health information with authorized health care entities. More than 70 primary care physicians are employed at UMHS clinics throughout central Missouri and, in 2012, serviced approximately 553,300 patient visits.

The Department of Family and Community Medicine (FCM) oversees six clinics, delivering over 100,000 patient visits. The Department of Internal Medicine (IM) oversees two clinics with no information reported on the number of patient visits. UMHS' EHR contains databases that include data from the university's hospitals and clinics. Within the EHR, the medication history allows providers to electronically and securely access details about a given patient's prescription, limited to the data collected. Basing our study on the existing medication history available in one of the most wired health care systems makes the aim of this study relevant and achievable.

Demographic and Satisfaction Survey

To divide responses into various demographically-based groups, the survey requested demographic data from participants prior to displaying survey questions. Demographic data collected included:

1. Gender
2. Age
3. Computer skills
4. Experience with any other EHR than PowerChart
5. Number of years as a professional health care provider

Data Analysis

Data from the survey were processed through tools built into Qualtrics and imported into Microsoft Excel 2016 for organizing and determining binary responses to block questions. Final analysis was conducted using R for Mac and RStudio for Mac. Performance metrics were based on determining a significant decrease in task time and/or a significant increase in task correctness. A generalized linear mixed model for binary data was used to predict the likelihood the respondent will provide a correct response. The fixed effects were treatment or control and five randomized controlled blocks. A random intercept was fit for each individual.

Limitations

Sample size was a main concern for this survey. Due to time and funding constraints, a limited participation group was used for this survey. With more time and funding, a broader participation group might have been recruited. To

complete the survey within the given time frame, participants were chosen based on the researcher's past relationships with the UMHS departments. Participants were narrowed to attending physicians, residents, and nurse practitioners who have acknowledged they currently use electronic patient medication histories.

Contact with the participants was through email. Phone, direct mail, or other social communications methods outside of email were not used to solicit participation. Incentives were not used to solicit participation.

CHAPTER 4: PRESENTATION AND ANALYSIS OF DATA

Introduction

In this chapter, the presentation and analysis of data from the purposive survey using block randomization is described. A purposive survey was used to test the effectiveness of a treatment visualization among a population of care providers. The data for the characteristics of participants, time to respond, and question response were collected using Qualtrics. The average time to complete all five block questions was 3.53 minutes per participant. All responses and time tracking was collected automatically using Qualtrics.

Disqualified Observations

The survey was activated a total of 35 times. Of those activations, 24 participants completed the demographics survey questions. Of those participants, one participant dropped out and for that participant no responses were collected across any block. Of the remaining 23 participants, two participants dropped out at BLOCK 5 and no responses was collected. One response to BLOCK 1 was intentionally removed because the response time was 71035 seconds (19.76 hours), 256 times greater than the next longest response time. The participant's responses remaining block responses did not produce a noticeable outlier; and including or excluding these responses did not change the outcome significance of the study. Therefore, the remaining responses from this participant were included in the final model.

Characteristics of Participants

Twenty-three participants consented, enrolled in the study, and completed at least three of the five block questions. Table 2 shows the collected demographics of 23 resident physicians, attending physicians, and nurse practitioners that participated in the survey, presented as percentages. Examined demographics include gender, age, computer skills, user of any EHR other than Cerner's PowerChart and years of experience as a health care provider.

Table 2: Demographics of 23 Survey Participants.

DEMOGRAPHICS		
GENDER		
MALE	12	(52%)
FEMALE	11	(48%)
AGE		
24-34 YEARS OLD	6	(26%)
35-44 YEARS OLD	4	(17%)
45-54 YEARS OLD	5	(22%)
55-64 YEARS OLD	7	(30%)
65-74 YEARS OLD	1	(4%)
COMPUTER SKILL		
BEGINNER	1	(4%)
INTERMEDIATE	18	(78%)
EXPERT	4	(17%)
USER OF ANY EHR OTHER THAN CERNER'S POWERCHART		
YES	17	(74%)
NO	6	(26%)
YEARS OF EXPERIENCE AS A HEALTH CARE PROVIDER		
0-5 YEARS	6	(26%)
6-10 YEARS	3	(13%)
11-20 YEARS	3	(13%)
21 YEARS OR MORE	11	(48%)

Distribution of Treatment versus Control Visualization

A total of 112 observations were collected across 23 participants. Of the 112 observations, the treatment visualization was randomly presented to participants 63 times. Table 3 displays the distribution of observations in total across blocks, by treatment, and by control.

Table 3: Count of Total Observations, Treatment Observations, and Control Observations in Aggregate and for Each Block

	TOTAL OBSERVATIONS	TREATMENT OBSERVATIONS	CONTROL OBSERVATIONS
ALL BLOCKS	112	63	49
BLOCK 1: CURRENT RX	22	14	8
BLOCK 2: PAST RX	23	11	12
BLOCK 3: TIME ON RX	23	14	9
BLOCK 4: NEW RX IN INTERVAL	23	13	10
BLOCK 5: RX IN INTERVAL	21	11	10

Block Responses

For the purposes of this study, the time variable is recorded as continuous and the response variable is recorded as binary. Determining a successful response required the participant to answer the whole question correctly and partial credit was not applied. Table 4 displays the mean task time +/- standard deviation and the task correctness. Please refer to Chapter 3 and the

development of questions to confirm concepts and specific questions used for each randomized block.

Table 4: Population Size, Mean Task Time, and Percentage of Correct Responses for Control and Treatment Participants across Blocks.

	POPULATION	MEAN TASK TIME (IN SECONDS)	TASK CORRECTNESS
ALL BLOCKS			
CONTROL	49	1366.30+/-10.35	30.61%
TREATMENT	63	1773.23+/-10.40	66.67%
BLOCK 1			
CONTROL	8	43.99+/-22.34	50.00%
TREATMENT	14	69.42+/-36.82	64.29%
BLOCK 2			
CONTROL	12	68.39+/-22.60	16.67%
TREATMENT	11	50.45+/-16.68	90.91%
BLOCK 3			
CONTROL	9	22.43+/-7.65	44.44%
TREATMENT	14	15.72+/-5.84	92.86%
BLOCK 4			
CONTROL	10	65.45+/-23.58	50.00%
TREATMENT	13	30.32+/-12.24	61.54%
BLOCK 5			
CONTROL	10	36.53+/-18.02	0.00%
TREATMENT	11	30.47+/-7.69	18.18%

Normalization of the Continuous Variable

One assumption made when fitting a linear model is that the errors from that model follow a normal Gaussian distribution.

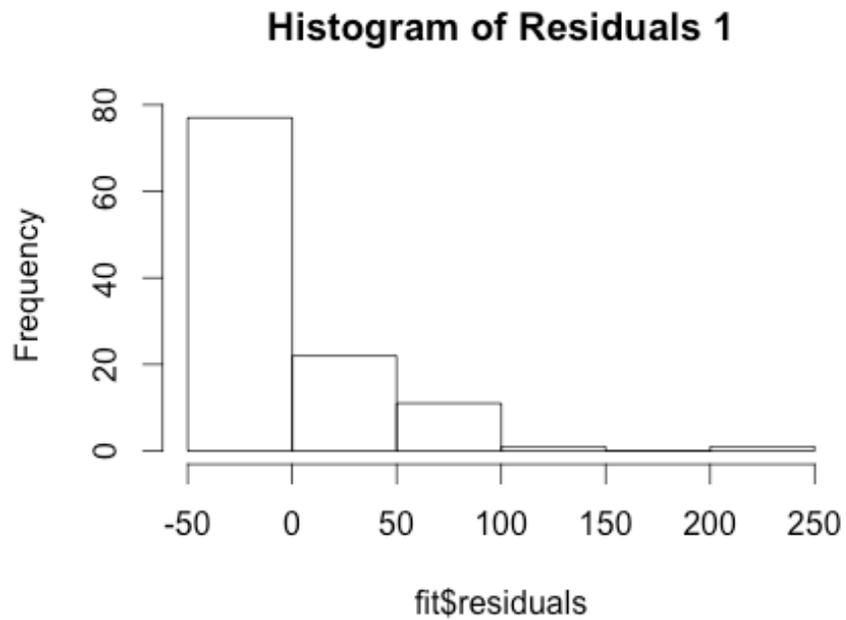


Figure 3: Histogram of Residuals from Model Fit on Non-Transformed Time Variable

The residuals from the one-way ANOVA model, using treatment, were not normally distributed. Thus, natural logarithm transformation was used against the time variable. Then, normality was checked against the transformed data using the same one-way ANOVA model. The residuals from the second model look normally distributed in Figure 4.

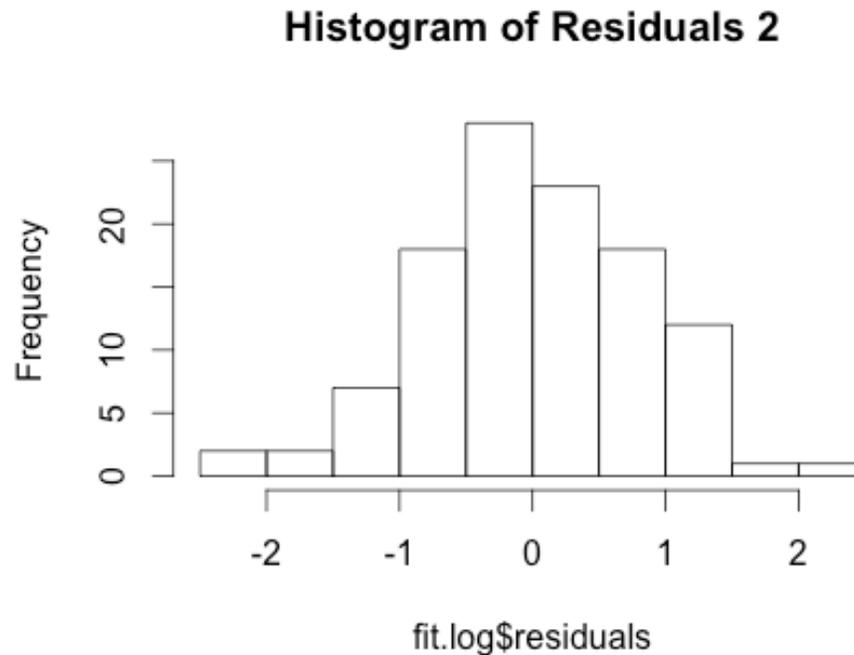


Figure 4: Histogram of Residuals from Model Fit on Natural Log Transformed Time Variable

Normalization of the Binary Variable

No transformation is required for the binary variable. The binary response variable (yes or no) is assumed to follow Bernoulli's distribution.

Modeling the Continuous (Time) Variable

The aim of this section is to determine if the treatment effect on the continuous (time) variable is significant after controlling for possible effects of the block or individual.

Determining the Final Model for Time

Every model tested was a linear mixed model which assumes a normally distributed response. The fixed effects are treatment and block. The random

effect was the individual. Two models were considered. The first model uses random intercept for individual. The second users random intercept term and random coefficient term for treatment. The purpose of using multiple models is to determine whether the difference in means of the time variable between control and treatment is significant. After fitting both models, the interpretation of the question of interest was the same. Therefore, because using the random coefficient term increases the complexity of the model without changing the outcome of the model, the final model does not use the random coefficient term.

Final Model for Interpreting Time Results

The final model is a linear regression with treatment, controlling for the fixed effects of block and the random effects of individual. The interpretation of estimate for intercept (Table 5) identifies the expected natural log time for a participant who did not receive a treatment in BLOCK 1 as 3.86853 log seconds. BLOCK 2-5 are included in the model along with the random intercept term for individuals solely to control for their effects when interpreting the results seen with treatment. The interpretation of the treatment estimate is an average natural log time difference of -0.14298 for a participant who received a treatment compared to a participant who received the control. The T-value is -1.313; thus the difference in average natural log time for treatment versus control is not great enough to conclude significance. After controlling for other factors in the model, there was not a significant relationship between treatment and log time.

Table 5: Output of Linear Regression Model with Random Intercept Term for Individual

	Estimate	Std. Error	T-value
(Intercept)	3.86853	0.16441	23.529
Treatment	-0.14298	0.10886	-1.313

Modeling the Binary (Response) Variable

The aim of this section is to determine whether the treatment effect on the binary (response) variable is significant after controlling for possible effects on the block or individual.

Determining Final Model of Response

Every model tested was a generalized linear mixed model which assumes a Bernoulli-distributed response. The fixed effects are treatment and block. The random effect was the individual. Two models were considered. The first model uses random intercept for individual. The second uses random intercept term and random coefficient term for treatment. The purpose of using multiple models is to determine whether the difference in means between the time variable for control and treatment is significant. After fitting both models, the interpretation of the question of interest was the same. Therefore, the final model does use the random coefficient term because the model did not converge.

Final Model for Interpreting Response Results

The final model is a generalized linear regression with treatment, controlling for the fixed effects of block and the random effects of individual. The interpretation of estimate for intercept (Table 6) identifies the average log odds

for a participant who did not receive a treatment in BLOCK 1 as -0.8568776 log odds. BLOCK 2-5 are included in the model along with the random intercept term for individual solely to control for their effects when interpreting the results seen with treatment. The interpretation of the treatment estimate is an average log odds difference of 2.1331515 for a participant who received a treatment compared to a participant who received the control. To interpret the log odds as probability, we use the formula $\frac{\exp(\log(odds))}{1+\exp(\log(odds))}$. The estimated probability for successfully responding to a question from a participant receiving treatment is $\frac{\exp(2.1331515-0.8568776)}{1+\exp(2.1331515-0.8568776)}$, or 0.7818148. The p-value is 0.000502; thus the difference in average log odds for treatment versus control is great enough to conclude significance. After controlling for other factors in the model, the mean difference between the average successful response for treatment versus the average successful response control is great enough to conclude significance.

Table 6: Output of Logistic Regression Model with Random Intercept Term for Individual

	ESTIMATE	STD. ERROR	Z-VALUE	P-VALUE
(INTERCEPT)	-0.8568776	0.6854798	-1.25	0.211285
TREATMENT	2.1331515	0.6129959	3.48	0.000502

CHAPTER 5: SUMMARY, DISCUSSION, AND IMPLICATION OF FINDINGS

Introduction

The findings are summarized and discussed in this chapter. The limitations, conclusions, implication for research and practice, and recommendations for future research are also presented. The purpose of this study is to answer the following questions:

- 1) Does introducing a new medication history visualization reduce the task time of a participant?
- 2) Does introducing a new medication history visualization increase the probability of correctly responding to medication questions?

Findings

The following paragraphs present the hypotheses that were tested and the results for each hypothesis.

Hypothesis one stated that by presenting a different visualization for a medication history, there would be a statistically significant decrease in the time to respond to questions using the treatment visualization when compared to the control visualization. After a natural log transformation normalized the results, there is an average natural log time difference of -0.14298 for a participant who received a treatment compared to a participant who received the control. However, the T-value is -1.313; thus the difference in average natural log time for

treatment versus control is not great enough to conclude significance. Therefore, hypothesis one is not accepted.

Hypothesis two stated that by presenting a different visualization for a medication history, there would be a statistically significant increase in the response accuracy to questions using the treatment visualization when compared to the control visualization. After using a generalized linear regression model, the likelihood of correctly responding to a question when presented with the treatment visualization is greater than the likelihood of responding correctly when presented with the control visualization with a p-value equal to 0.000502. Therefore, hypothesis two is accepted.

Limitations

Several limitations presented in testing the task time and task correctness of medication history visualizations.

1. Participation in the study was voluntary and limited to those participants who consent to the study electronically via the recruitment email. Data collection may have excluded some information belonging to those who did not enroll.
2. The sample size included 112 observations from 21-23 participants. If a significant result is observed, then the sample size is no longer an issue. If a non-significant result is observed, then either the sample is not large enough or the assumption that was tested is not correct. Perhaps calculating a statistical power in advance or obtaining a larger sample size would have provided a significant result for hypothesis one.

3. The generalizability of this study may be limited by the demographic information and sample size.
4. The study design excluded those participants without computer and internet connection.

Conclusion

Displaying medication history information using concatenated text and minimalistic icons does not aid in correctly responding to common medication questions. A combination of visualization techniques to graphically represent duration, change, and dosage level over time will aid physicians in correctly interpreting the information presented by an electronic medication history.

The average time to respond based on our findings was less with the treatment than with the control. However, the difference was not significant. More investigation is required to conclude correlation, but a potential explanation for the lack of significance is that the time required between treatment and control is equivalent with only an increase in accuracy.

Implications

This study evaluated two visualization approaches to see if one was more effective at decreasing the participant's task time or increasing task correctness. The results indicate that the treatment visualization increased the task correctness without a significant change in the task time.

The implications of this study suggest the effort for visualizing the medication history using the technique referenced in the study will produce

greater accuracy to common clinical questions at the point of care without significantly changing the time required to interpret the information. Therefore, electronic health record vendors and health care organizations should consider the benefits of increase accuracy against the effort to implement this new technology.

Future Research

1. The randomized block approach outlined in Chapter 3 can be used to identify significance when compared to cross-over designs and controlled experiments as in Aigner et al.^[31] and Wongsuphasawat et al.^[37]
2. The study should be replicated with a larger sample size to see if the findings are consistent.
3. The study should be conducted where treatment and control participants do not have familiarity with the control visualization.
4. The study should be conducted against participants without a medical background to determine if clinical expertise contributes to response accuracy.
5. The study should include interactive visualizations to determine if results vary based on a user's ability to manipulate the information.
6. The study should be conducted against other disciplines outside family and community medicine and internal medicine.

Summary

Chapter five has summarized the purpose of the study, the data collection procedures, statistical tests, and findings. The limitations, conclusion, implications, and recommendation for future study are also presented.

APPENDIX A: SURVEY QUESTIONNAIRE

Qualtrics Survey Software

12/31/15, 8:32 AM

Respondent

Browser Meta Info

This question will not be displayed to the recipient.

Browser: **Safari**

Version: **9.0.2**

Operating System: **Macintosh**

Screen Resolution: **1920x1080**

Flash Version: **20.0.0**

Java Support: **1**

User Agent: **Mozilla/5.0 (Macintosh; Intel Mac OS X 10_11_2) AppleWebKit/601.3.9 (KHTML, like Gecko) Version/9.0.2 Safari/601.3.9**

Gender

Male Female Other

Age

24-34 years old 35-44 years old 45-54 years old 55-64 years old 65-74 years old
75 years and older

Computer Skills

No computer skill Beginner Intermediate Expert

Experience with any EHR other than Cerner's PowerChart

Yes No

<https://missouri.qualtrics.com/ControlPanel/Ajax.php?action=GetSurveyPrintPreview>

Page 1 of 16

Number of years as a professional healthcare provider

0-5 years 6-10 years 11-20 years 21 years or more

Identify Current Rx

These page timer metrics will not be displayed to the recipient.

First Click: *0 seconds*

Last Click: *0 seconds*

#QuestionText, TimingPageSubmit#: *0 seconds*

#QuestionText, TimingClickCount#: *0 clicks*

Based on the visualization provided, please identify which of the following **is not** a currently prescribed medication?

OrderName	Details	Last Updated
<input checked="" type="checkbox"/> alendronate (alendronate 70 mg oral tablet)	70 mg 1 Tablet(s), Oral, qWeek , # 12 Tablet(s), Refill(s) 3, Pharmacy: Mizzou Courtyard	1/5/15 10:14
<input checked="" type="checkbox"/> allopurinol (allopurinol 300 mg oral tablet)	300 mg 1 Tablet(s), Oral, Daily, #90 Tablet(s), Refill(s) 3, other	1/5/15 10:14
<input checked="" type="checkbox"/> aspirin (aspirin 81 mg oral tablet)	81 mg 1 Tablet(s), Oral, Daily, # 90 Tablet(s), Refill(s) 3, Pharmacy: Mizzou Courtyard	1/5/15 10:14
<input checked="" type="checkbox"/> atorvastatin (atorvastatin 40 mg oral tablet)	40 mg 1 Tablet(s), Oral, Daily, # 90 Tablet(s), Refill(s) 3, high cholesterol, Pharmacy: Miz...	1/5/15 10:14
<input checked="" type="checkbox"/> chlorthalidone (chlorthalidone 25 mg oral tabl...	25 mg 1 Tablet(s), Oral, Daily, # 90 Tablet(s), Refill(s) 3, high BP, Pharmacy: Mizzou C...	1/5/15 10:14
<input checked="" type="checkbox"/> escitalopram (escitalopram 10 mg oral tablet)	10 mg 1 Tablet(s), Oral, Daily, # 90 Tablet(s), Refill(s) 3, high BP, Pharmacy: Mizzou C...	5/9/14 10:14
<input checked="" type="checkbox"/> levothyroxine (levothyroxine 100 mcg [0.1...	100 mcg 1 Tablet(s), Oral, Daily, # 90 Tablet(s), Refill(s) 3, Hypothyroidism, Pharm...	1/5/15 10:14
<input checked="" type="checkbox"/> losartan (losartan 100 mg oral tablet)	100 mg 1 Tablet(s), Oral, Daily, # 90 Tablet(s), Refill(s) 3, high BP, Pharmacy: Mizzou C...	1/5/15 10:14
<input checked="" type="checkbox"/> meloxicam (meloxicam 10 mg oral tablet)	15 mg 1 Tablet(s), Oral, Daily, # 90 Tablet(s), Refill(s) 3, pain control, called to ph...	1/5/15 8:00
<input checked="" type="checkbox"/> metformin (metformin 1000 mg oral tablet)	1,000 mg 1 Tablet(s), Oral, bid # 180 Tablet(s), Refill(s) 3, diabetes, called to ph...	1/5/15 8:00

Chlorthalidone

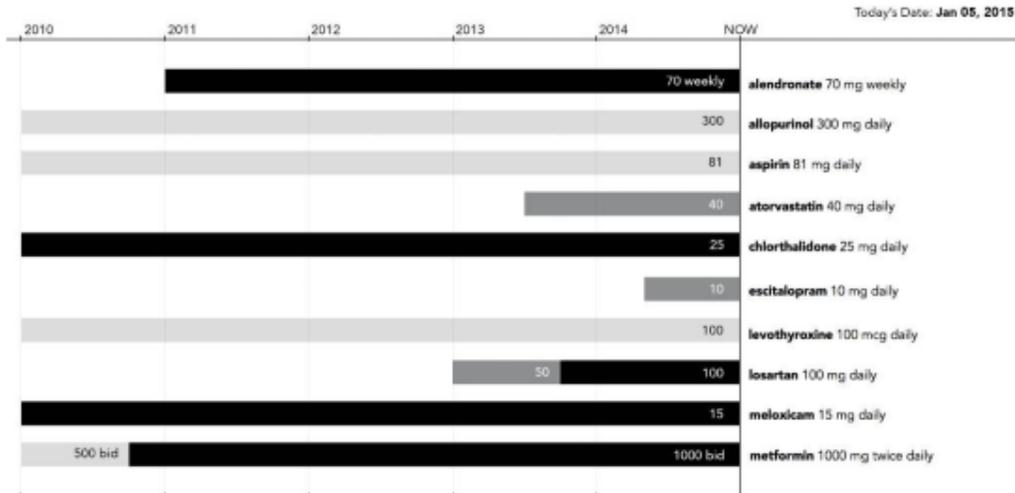
Lisinopril

Losartan

Metformin

Cannot Determine

Based on the visualization provided, please identify which of the following **is not** a currently prescribed medication?



- Chlorthalidone
- Lisinopril
- Losartan
- Metformin
- Cannot Determine

Identify Past Rx

These page timer metrics will not be displayed to the recipient.

First Click: 0 seconds

Last Click: 0 seconds

#QuestionText, TimingPageSubmit#: 0 seconds

#QuestionText, TimingClickCount#: 0 clicks

Based on the visualization provided, please check all past prescriptions.
Our definition of "past prescriptions" includes only medication(s) prescribed AND not currently in use.

Atorvastatin
 Chlorthalidone
 Escitalopram
 Lisinopril
 Metformin
 Rosuvastatin

Based on the visualization provided, please check all past prescriptions.
 Our definition of "past prescriptions" includes only medication(s) prescribed AND not currently in use.



Atorvastatin
Chlorthalidone
Escitalopram
Lisinopril
Metformin
Rosuvastatin

Length of Time on a Specific Drug

These page timer metrics will not be displayed to the recipient.

First Click: *0 seconds*

Last Click: *0 seconds*

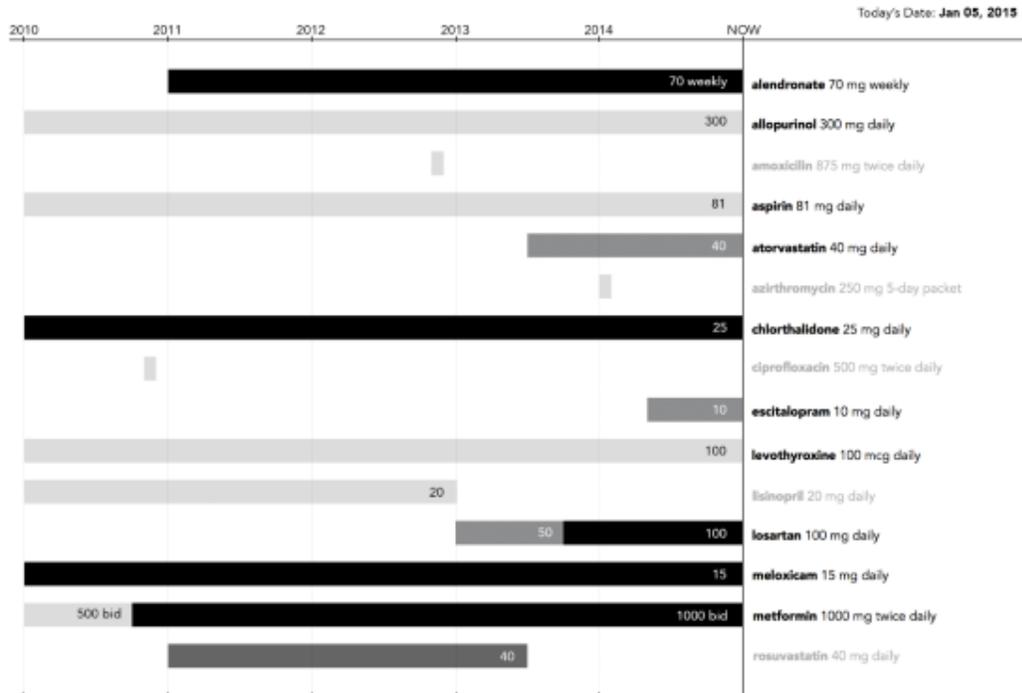
#QuestionText, TimingPageSubmit#: *0 seconds*

#QuestionText, TimingClickCount#: *0 clicks*

Based on the visualization provided, how many years has Alendronate been prescribed to the patient?

- 4 years
- 5 years
- 6 years

Based on the visualization provided, how many years has Alendronate been prescribed to the patient?



- 3 years
- 4 years

5 years

6 years

Identify New Medication in a Given Timeframe

These page timer metrics will not be displayed to the recipient.

First Click: *0 seconds*

Last Click: *0 seconds*

#QuestionText, TimingPageSubmit#: *0 seconds*

#QuestionText, TimingClickCount#: *0 clicks*

Based on the visualization, select all medications newly prescribed during 2012.

- Amoxicilin-Clavulanate
- Aspirin
- Atorvastatin
- Metformin
- None of these

Based on the visualization, select all medications newly prescribed during 2012.



- Amoxicilin
- Aspirin

Atorvastatin
Metformin
None of these

Identify Dosage Change in a Given Timeframe

These page timer metrics will not be displayed to the recipient.

First Click: *0 seconds*

Last Click: *0 seconds*

#QuestionText, TimingPageSubmit#: *0 seconds*

#QuestionText, TimingClickCount#: *0 clicks*

Based on the visualization, identify all medications with a dosage change during 2013.

- Atorvastatin
- Losartan
- Meloxicam
- None of these

Based on the visualization, identify all medications with a dosage change during 2013.



- Alendronate
- Atorvastatin
- Losartan

Meloxicam
None of these

Powered by Qualtrics

APPENDIX B: IRB EXEMPT APPROVAL LETTER



Institutional Review Board
University of Missouri-Columbia

190 Galena Hall; Dc074.00
Columbia, MO 65212
573-882-3181
irb@missouri.edu

August 4, 2015

Principal Investigator: Andrew Hargrove Hutson
Department: SHP/Health Sciences

Your Exempt Application to project entitled Measuring the Speed and Efficacy of Clinical Decision Making based Medication History Data Visualizations was reviewed and approved by the MU Institutional Review Board according to terms and conditions described below:

IRB Project Number	2003333
IRB Review Number	207133
Approval Date of this Review	August 04, 2015
IRB Expiration Date	August 04, 2016
Level of Review	Exempt
Project Status	Active - Open to Enrollment
Exempt Categories	45 CFR 46.101b(2)
Risk Level	Minimal Risk
Internal Funding	Personal funds

The principal investigator (PI) is responsible for all aspects and conduct of this study. The PI must comply with the following conditions of the approval:

1. No subjects may be involved in any study procedure prior to the IRB approval date or after the expiration date.
2. All unanticipated problems, adverse events, and deviations must be reported to the IRB within 5 days.
3. All changes must be IRB approved prior to implementation unless they are intended to reduce immediate risk.
4. All recruitment materials and methods must be approved by the IRB prior to being used.
5. The Annual Exempt Form must be submitted to the IRB for review and approval at least 30 days prior to the project expiration date. If the study is complete, the Completion/Withdrawal Form may be submitted in lieu of the Annual Exempt Form
6. Maintain all research records for a period of seven years from the project completion date.
7. Utilize all approved research documents located within the attached files section of eCompliance. These documents are highlighted green.

If you have any questions, please contact the IRB at 573-882-3181 or irb@missouri.edu.

APPENDIX C: APPROVED RECRUITMENT EMAILS

Initial Email

Researcher's Name(s): Andrew Hutson

Project Number: 2003333

Project Title: Measuring the Speed and Efficacy of Clinical Decision Making based Medication History Data Visualizations

You are being asked to participate in a research study to determine if changing the presentation of medication history information increases the speed of responding to common clinical questions. If you are willing to participate please click the link below and respond to a series of demographic questions followed by five (5) questions based on a randomly assigned visualization. Each question will randomly show a tabular view (existing) or a timeline view (new) medication history visualization. Because the visualizations are large, you must take this survey on a larger screen, instead of using a mobile device.

This study will take approximately five (5) minutes to complete. Participation is voluntary and you can stop participating at any time without penalty.

Please contact Andrew Hutson (ahhhw5@mail.missouri.edu) if you have questions about the research.

If you have any questions regarding your rights as a participant you may contact the University of Missouri Institutional Review Board at (573) 882-3181 or irb@missouri.edu.

Follow-up Email

This is a follow up reminder for an email that was sent on ??/??/2015. Please disregard if you have already opted in or opted out of this survey.

Researcher's Name(s): Andrew Hutson

Project Number: 2003333

Project Title: Measuring the Speed and Efficacy of Clinical Decision Making based Medication History Data Visualizations

You are being asked to participate in a research study to determine if changing the presentation of medication history information increases the speed of responding to common clinical questions. If you are willing to participate please click the link below and respond to a series of demographic questions followed by five (5) questions based on a randomly assigned visualization. Each question will randomly show a tabular view (existing) or a timeline view (new) medication history visualization. Because the visualizations are large, you must take this survey on a larger screen, instead of using a mobile device.

This study will take approximately five (5) minutes to complete. Participation is voluntary and you can stop participating at any time without penalty.

Please contact Andrew Hutson (ahhhw5@mail.missouri.edu) if you have questions about the research.

If you have any questions regarding your rights as a participant you may contact the University of Missouri Institutional Review Board at (573) 882-3181 or irb@missouri.edu.

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VITA

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