

AHRQ Grant # R21HS019023

VisualDecisionLinc: Real-time Decision Support in Behavioral Health

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Dates of Project

08/01/2011 - 01/31/2013

Federal Project Officer: Charlotte Mullican, AHRQ

Acknowledgement

We are thankful to the Agency for Healthcare Research and Quality (AHRQ) for their support of this research.

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1. Abstract

The awarded work explored the use of visual analytics with real-world observational data to better understand and develop: sense-making formats for data attributes to facilitate easy interpretation; methods to identify, display, and rapidly process comparative evidence to provide customized, concise, and effective clinical decision support; real-time systems for coupling clinical guidelines with data-driven evidence; processes to incorporate clinical warehouse data as a supplemental resource for clinical decision support; and approaches for designing user interfaces (UIs) that integrate with the clinician's workflow and enable real-time decision making. Specifically, we designed and developed approaches to identify, aggregate, and present treatment-response information on individual patients and comparative populations as 'data views'. We then aggregated these data views to build a visual analytics-based clinical decision support prototype: 'VisualDecisionLinc' (VDL). VDL was designed to improve clinical decision-making through the use of integrated data and knowledge derived from electronic medical records (EMRs).

2. Purpose

The awarded work used real-world observational data derived from the MindLinc EMR system (developed by Duke University Health System) to:

- Identify different data attributes and approaches for the stratification of comparative populations to select best treatment options for individual patients.
- Explore predictive analytics for treatment outcomes.
- Develop user-friendly UIs to present the identified evidence.
- Design and develop methods to facilitate clinical decision-making processes in real-time and under real-world scenarios.
- Evaluate the developed UIs through usability studies.

3. Scope

We used anonymized patient data from MindLinc—the largest available warehouse of psychiatry data—for the design and development of the VDL clinical decision support prototype. We focused on a subset of patients with a primary diagnosis of Major Depressive Disorder (MDD).

4. Infrastructure Setup and Data Formatting

4.1. Infrastructure Setup

The initial setup involved the aggregation of de-identified patient data from the multiple

clinical data sets that were available as part of MindLinc. For scalability and to port the data, we designed an in-house VDL SQL database layer that preserved the table relationships that existed within the MindLinc SQL Server database.

4.2. Data Cleaning & Formatting

We addressed multiple data quality issues (e.g., data element misspellings, missing data, data integration problems, etc.) before we could use the data to design the VDL application. We also developed different approaches to import and improve the quality of the data. Specifically, Lookup tables and custom functions were implemented to automate the clean-up operations and provide consistent, analysis-ready data.

5. Work Performed

5.1. Set of Similarity Attributes (SSAs) for Comparative Evidence (Aim 1)

In consultation with physician as experts, we identified a set of data-filtering attributes: demographics (age, gender, race); comorbidities (related to MDD like – mood disorder, anxiety disorder, substance use disorder, and others); and prescribed medications. Initially, we focused on single medication data. Later, we extended our approach to include multiple medication combinations, which is more realistic for patients with MDD. Because of the large number of potential medication combinations, we adopted an approach that relied on medication classes. Thirteen distinct medication classes were identified, and all individual medications were classified into one of the identified classes. These medication class information were used as a SSA data attribute to narrow down treatment choices.

5.2. Design and Development of Analytical Engine Layer for Integration (Aim 1)

The identified SSAs was used to design and build the analytical engine. As part of the setup, we designed the analytical engine with the ability to directly query the database. At the UI level, this setup provided an individual clinician with the option of altering data selection (include/exclude data elements) based on need and interest. We designed the analytical engine such that any change in the SSAs invokes an action to instantly update the comparative population. The developed analytical engine directly contributed to the dashboard developed as part of Aim 2.

5.3. Exploration of Techniques for Predictive Analytics (Aim 1)

We developed a model to evaluate the quality of psychiatric care using data available in the MindLinc database. The model used a specific health outcome variable—Clinical Global Impression (CGI)—as a measure of patient status and treatment response. More than 500,000 patient records containing CGI and predictor data were identified in the MindLinc database and used for proportional-odds model estimation. The set of predictive data attributes included

demographic information, comorbidities, past medical history, medications, and health outcome (CGI value). Significant estimates were found for predictors from all groups. We published the results of our predictive analysis.

5.4. Exploration of Data-driven Approach to Identify and Display Data - (Aim 1, Aim 2)

a. Treatment Outcome with Medication Overview: We implemented a strategy to categorize patients on the basis of health outcome (CGI value) with respect to medication. Data were analyzed and presented as scatter plots, with patient data on pre-medication status on the x-axis and resultant treatment outcome on the y-axis. The plots revealed no association between medication and treatment outcome.

b. Treatment Outcome with Medication Class Overview: The initial dataset was then stratified at the medication class level. As in (5.4.a), data were analyzed and presented as scatter plots, with patient data on pre-medication status on the x-axis and resultant treatment outcome on the y-axis. For most medication classes, the plots revealed no association between medication class and treatment outcome.

c. Treatment Outcome with Medication Class by Gender: We implemented a strategy to build density plots using the medication class data from (5.4.b). A few of the density plots showed an interesting trend, with a change in medication resulting in a worse outcome. To explore outcome trends by gender, we stratified the dataset by gender and generated density plots with patient status values pre- and post-medication. Preliminary analysis of density plots showed an interesting trend in which a change in medication resulted in a slightly worse outcome for females than males.

d) Outcome Transition Trend to Build Patient Groups: We then categorized the patient population into three distinct groups: (a) patients who experienced a worst outcome or increase in CGI response; (b) patients who experienced a worst outcome, but transitioned to a normal treatment outcome; and (c) patients who did not experience a worst outcome. We explored trends in the data with respect to the following:

- Age-group vs. gender
- Age-group vs. race
- Within each age group, and across all age groups, is there a difference in the incidence of MDD by gender? Within each race, is there a difference in the incidence of MDD by gender?
- Do patients of certain age groups show more MDD conditions?
- Does treatment outcome in response to a given medication class vary among the three

patient subgroup identified earlier?

We used a clustering approach and multi-dimensional scaling to determine if distinct cluster patterns emerge across all identified patient subgroups and if there is a variable that contributed significantly to the variation in the dataset. No variable distinctly popped out.

5.5. Data View: Treatment Progress and Outcome with Context (Aim2)

We redesigned the timeline view to show the trend in CGI over time. To build contextual information, we started with a visual overlay of the patient visit type data (inpatient, outpatient, emergency). This approach will be extended to show other contextual patient-centric data.

5.6. Data View: Treatment Recommendation (Aim 2)

We designed the treatment-response component to provide insight into the effectiveness of different medications in the comparative population. The algorithm we developed is designed to aggregate and summarize outcome data on the prescribed medications in the identified comparative population. At the UI level, the summarized information is presented in the form of ‘% patients improved’, with additional contextual information provided. In our initial attempt, we focused on treatment response to a single medication in the comparative patient population. We later modified the approach to include the treatment response to multiple medication combinations in the comparative patient population.

5.7. Data View: Comorbid Conditions with Option to Filter (Aim 2)

We developed an algorithm to scan data on patient profiles and quantify comorbid conditions for the patient and comparative population. At the UI level, visual color codes (red = same as patient, black = population cohort conditions, gray = no part of the current pool of patient cohort) were used to display similarities and differences in comorbid conditions. We embedded a filtering option at the UI level to define *ad hoc* inclusion/exclusion criteria for the comparative population.

5.8. Data View: Treatment Outcome Projections (Aim2)

We designed an algorithm to identify a comparative patient population that received prescribed medications for a relatively long time period (at least 120 days). Additional logic is embedded within the algorithm to align the filtered comparative patient data and aggregate their treatment response to a given medication at 30-, 60-, 90-, and 120-day time stamps. The median value was computed from the aggregated values at each time stamp to show the projected treatment response at 30-, 60-, 90-, and 120-day time stamps.

5.9. Coupling UI and Analytical Engine (Aim 2)

The analytical engine is an integrated component of the dashboard-style UI that is designed to provide an overview of the patient’s status and evidence from a comparative population (**Figure 1**). The analytical engine is built as a data-query layer, with SSAs used to facilitate *ad hoc*

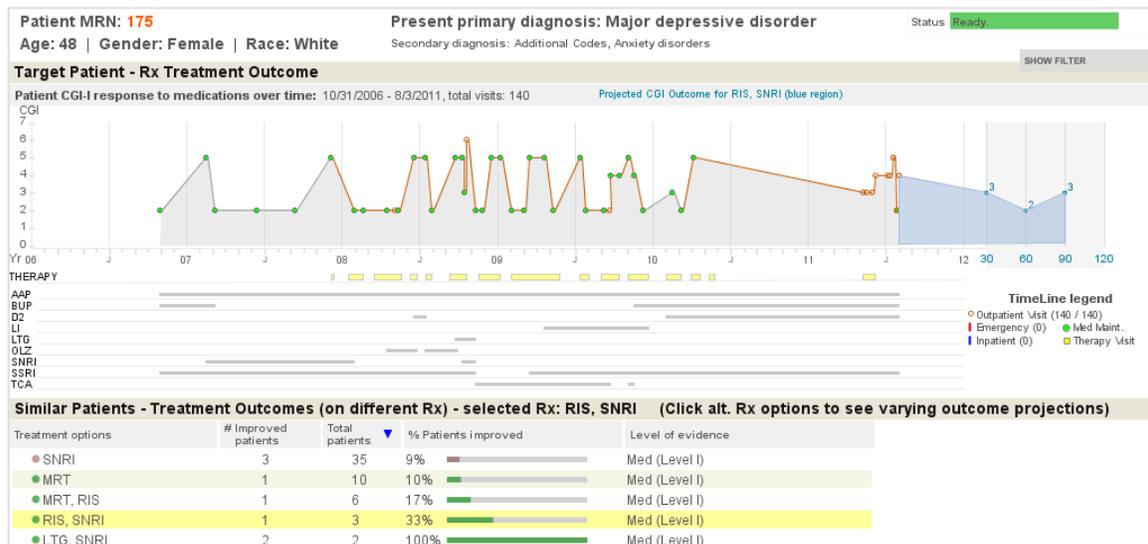


Figure 1: Dashboard with integrated data views to show: individual patient information, including primary and comorbid conditions; health outcome to different prescribed medications; medications prescribed to a similar (or comparative) patient population; and predicted outcome with different treatments for the individual patient.

filtering of the comparative population and build different data views. We designed approaches to couple the patient view with the updatable view of the comparative population.

5.10. Data View: Filters and Coupling with Other Views (Aim 2)

We included the initial SSAs as filters to help define the comparative population. Further, we developed the coupling layer that integrates all of the different data views. With this coupling layer in place, any change to the selected SSAs in the data view automatically updates all other data views to reflect the filtered data.

5.11. Iterative Design Approach for Multiple Data Views & UI Changes (Aim 2)

We made design changes at the UI level to incorporate data on multiple medications. The main changes were in the treatment-response component. Also, the underlying algorithm was modified to enable the exchange of the multiple medication data with the other connected data views.

5.12. Data View: Clinical Guideline Component (Aim 2)

We used the treatment guidelines used in the treatment of MDD. For the initial prototype, we designed the entire workflow needed to map patient data to the guidelines (**Figure 2**); this included: a coordinate profile of the nodes and flow based on the protocol; a mapping engine logic to map patient data to different stages in the protocol; and a renderer to overlay patient data onto the guideline. We then extended our approach to include data from the comparative patient population.

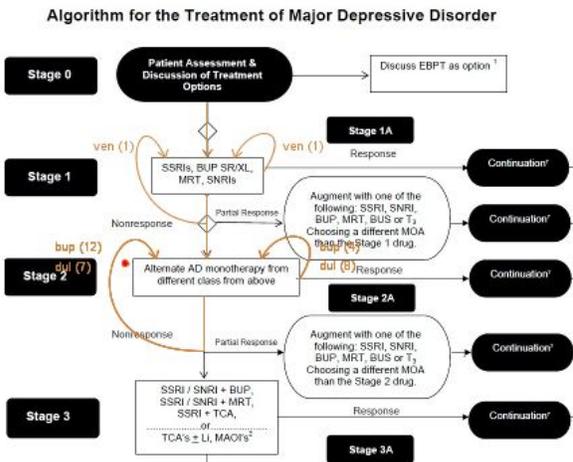


Figure 2: Patient treatment and outcome data are mapped to the recommended treatment guideline.

5.13. Data View: Compressed Guideline Design (Aim 1 and Aim 2)

Using the TMAP guidelines, the abstract view was designed to include three bins: (a) single medication bin; (b) two medication combination bin; and (c) multiple medication combination or other combination bin. Building on our initial patient mapping workflow, we optimized the decision engine logic to map patient data to different bins. Using the mapping workflow, we were able to retrospectively map patient data to the abstract view of the TMAP guidelines. To quickly show the treatment outcome (CGI values), we color-coded individual prescribed medication combinations with green background color to reflect condition improvement or red to reflect condition worsening (**Figure 3**).



Figure 3: Design of a compressed guideline representation for the rapid interpretation of treatment outcome by medication or medication combination. Green = condition improvement; red = condition worsening.

5.14. Integrated Compressed Guideline to modified UI (Aim 2)

We integrated the abstract view of the guideline as part of the redesigned UI. Modifications were made to tightly integrate medications with the timeline view. An interaction code was added to individual prescribed medication cells to trigger the display of the time period(s) that the selected medication was prescribed.

5.15. IRB Approval and Recruitment (Aim 3)

We submitted a new IRB application to Duke to conduct usability evaluation in mid-December 2011 and received approval in early February. The IRB approval allowed us to evaluate the UI. Our initial screening involved potential participants with various backgrounds (MD, PhD, social worker).

5.16. Preparation for Initial Evaluation Study (Aim 3)

We prepared a demonstration video with an explanation on the use of the VDL UI. The demonstration video is intended to reduce variability and bias in the usability analysis, such that the evaluation reflects the evaluator's response to the UI rather than the explanation provided by the investigative team.

5.17. Initial Evaluation Study of the UI (Aim 3)

We adopted a combination of agile methodology, action research, and cognitive task analysis in our evaluation. First, rather than relying strictly on evaluation results derived from a highly selected, large group of participants, the agile approach involves iterative and incremental evaluation involving cycles of evaluation, each with a small number of participants and iterative updates to the system design. Second, the action research approach involves environments that are as realistic as possible, thus avoiding artificial testing environments that usually do not match the real-world environments. We also intentionally avoided the use of focus groups, in which participants speculate on what they intend to do rather than what they actually would do. For the first cycle of evaluation, we recruited three participants. Each reviewed the video that highlighted the UI features. Afterward, we provided participants with data on a simulated patient and asked them to interact with the UI and provide verbal feedback. Participant interaction with the UI and verbal feedback were captured using a screen-capture tool.

5.18. Analysis and Summary of the Initial Evaluation Study (Aim 3)

We carried out a qualitative analysis of the participant data using DEDOOSE, which is a web-based qualitative analysis tool for grounded theory. Each video was coded and classified into categories to analyze, and identify the development of overarching themes. Lessons learned from the initial UI evaluation were used to make changes the UI.

5.19. Redesign of the UI for Second Evaluation Study (Aim 2)

Using the results of our initial evaluation, we revised the UI to show and communicate clearly

the information shown by each view. Specifically, we added functionality to incorporate additional filters in order to reduce the information clutter at the UI level. The new UI was packaged and made ready for the second evaluation study.

5.20. Coordination of the User Group for Second Evaluation Study (Aim 3)

The second evaluation study involved more refined evaluation methodology to better explore the usability of the UI. We developed new task questions to evaluate how well the VDL UI aligns with the clinician's actual workflow. Task questions similar to one shown here were used - 'Interact with the Guidelines Mapped to Patient view and determine the number of days the combination 'AAP, TCA' was prescribed. We also added UI features and created a very formal setting to communicate information more effectively and better mimic real-world scenarios. We decided to narrow our participant pool to include only those subjects with a medical background (MD, RN) because this group is most likely to use an EMR system on a daily basis. Six subjects were recruited and completed the evaluation study.

5.21. Analysis and Summary of Second Evaluation Study (Aim 3)

The pre- and post-test results were recorded and analyzed. Overall, the results were encouraging. The participants liked the different data views and the ability to customize the evidence to meet their needs. The evaluation results were published as a AMIA workshop paper.

6. Dissemination

6.1. Journal [J] & Conference Publications

1. [J1] Mane, K. K., Bizon, C., Owen, P., Gersing, K., Mostafa, J., and Schmitt, C. (2011) Patient Electronic Health Data–Driven Approach to Clinical Decision Support. *Clinical and Translational Science Journal*, 4 (5): 369–371.
2. [J2] Mane, K. K., Bizon, C., Schmitt, C., Owen, P., Burchett, B., Pietrobon, R., and Gersing, K. (2012) VisualDecisionLinc: A Visual Analytics Approach to Comparative Effectiveness–based Clinical Decision Support in Psychiatry. *Journal of Biomedical Informatics*, 45 (1): 101–106.
3. (ACM Conference) Mane, K., Owen, P., Bizon, C., Schmitt, C., and Gersing, K. (2012) Mapping Patient Treatment Profiles and Electronic Health Records to a Clinical Guideline for Use in Patient Care. In *Proceedings of the 2nd ACM SIGHIT International Health Informatics Symposium (IHI 2012)*, ACM, New York, USA. pp 369–371.
4. (Intl. Conference) Mane, K., Schmitt, C., Owen, P., Gersing, K., Ahalt, S., and Wilhelmsen, K. (2012) Data-driven Approaches to Augment Clinical Decision in EMR Era. 3rd International Workshop on Cognitive Information Processing (CIP 2012), Spain, May 28-30, 2012, pp. 1–5.

5. (ACM BCB 2013 - Conference) Mane, K., Owen, P., Schmitt, C., Wilhelmsen, K., Gersing, K., Pietrobon, R., and Akushevich, I. (2013) Visual Analytics to Optimize Patient-Population Evidence Delivery for Personalized Care. 4th ACM International Conference on Bioinformatics, Computational Biology, and Biomedical Informatics (ACM BCB 2013), Washington DC, September 22-25, 2013.
6. (ACM-BCB Conference) Akushevich, I., Kravchenko, J., Gersing, K., and Mane, K. (2013) Predictive Model of the Treatment Effect for Patients with Major Depressive Disorder. 4th ACM International Conference on Bioinformatics, Computational Biology, and Biomedical Informatics (ACM BCB 2013), Washington DC, September 22-25, 2013.
7. (AMIA-Visual Analytics) Mane, K., Carrasco, V., and Mostafa, J. (2013) Visual-based Interactive Clinical Decision Support Tools: Developing User-centric Approaches. American Medical Informatics Association (AMIA) 2013 Annual Symposium - Workshop on Visual Analytics in Healthcare, Washington, DC, November 16, 2013, pp. 19–23

6.2. Poster Presentations

1. (AMIA Poster) Visual Mapping of Patient Medical Profile to Clinical Guideline. American Medical Informatics Association (AMIA) 2011 Annual Symposium, Washington, DC.
2. (Poster) A Paradigm Shift: Electronic Health Records Data in Clinical Practice. CTSA 2011 Annual Meeting, NIH Campus, Bethesda, MD.
3. A Paradigm Shift: Electronic Health Records Data in Clinical Practice. CTSA 2011 Annual Meeting, NIH Campus, Bethesda, MD.
4. (AMIA Poster) Compact Clinical Guideline: Representation and its Use in Clinical Care. American Medical Informatics Conference (AMIA) 2012 Annual Symposium, Chicago, IL (selected as Distinguished Poster).
5. (Poster - AcademyHealth) Methodological Challenges for Evaluating Visual Approaches for Clinical Data Access. EDM-Academy Health Symposium, Baltimore, MD.

6.3. Presentation Talks

1. (Health DataPalooza Presentation) Data-driven Approach to Augment Clinical Decision

Making at the Point of Care. Presented at the Health Data Initiative Forum III – The Health DataPalooza, Washington, DC, June 5, 2012 (<http://www.hdiforum.org/>).

2. (Panel Talk/Presentation) Panel: Mining of EHRs, Challenges, and Payoffs. NCHICA, 7th Academic Medical Center Conference, 2011 (<http://www.nchica.org/Activities/AMC2011/agenda.htm>).
3. (Presentation) Evidence-based Medicine at the Point-of-Care: Using Informatics in the EHR Era. North Carolina Network Consortium event on Emerging Issues in Chronic Disease in Primary Care, Greensboro, NC, March 2012 (http://www.ncnc.unc.edu/primarycare_program.pdf).
4. (AHRQ) Panel presentation at AHRQ event, 27th National Web Conference on Enhancing Behavioral Health Using Health IT, February 2013.
5. (Presentation) Presentation at the BRIC Research Day event, UNC – Chapel Hill, 2013

6.4. Book Highlight

- VisualDecisionLinc User Interface, highlighted in health informatics book, “Health Analytics: Gaining the Insights to Transform Healthcare”, by Jason Burke, August 2013.

6.5. Award

- NCHICA-Intel Health Innovation Award (in top 3 finalists).

7. Synergistic Activities

The knowledge and technologies developed as part of this project are being translated to design novel approaches to improve treatment outcomes for patients with another chronic condition, pediatric epilepsy. That project involves researchers and clinicians from the Departments of Neurology at three major academic centers—Children’s Hospital in Boston (Harvard), Duke University, and the University of North Carolina at Chapel Hill. Many more interesting ventures are being explored as a result of this project.