Valleywise Health Final Report

AHRQ Challenge: Harnessing Data Visualization to Advance Equity in Clinical Services

Advancing Equity in Women's Depression Care: The Arizona EQUIDEM Data Visualization Project
August 26, 2024

Summary

The Arizona EQUIDEM (Equity in Depression care for Mothers) pilot project aimed to develop and test enhanced data visualization tools for monitoring and improving evidence-based depression care for pregnant and postpartum women (PPW). Using the Plan-Do-Study-Act cycle, Valleywise Health and Arizona State University collaborated to design SQL queries, validate data through a large language model, and create user-centered dashboard visualizations using synthetic data. These tools, including a daily huddle report and a monthly performance scorecard, were developed with input from clinicians and staff and tested within a women's health clinic, proving to be both valuable and feasible. Valleywise Health will continue this research by demonstrating the tools with real, de-identified patient data in the coming months. To sustain the initiative, a sustainability plan has been developed, establishing a data pipeline, implementing continuous improvement strategies, and conducting a cost-benefit analysis to ensure long-term viability.

Background

Depression Care Recommendations. The EQUIDEM project aligns with depression care recommendations from the US Preventive Services Task Force (USPSTF). USPSTF recommends depression screening for all adults and behavioral health counseling for perinatal depression. Depression screening and a documented follow-up plan for positive screenings is an electronic clinical quality measure (CMS2v11), part of the Uniform Data System and recommended by the U.S. Bureau of Primary Health Care. Benefits of depression screening include early identification, improved treatment access, reduced healthcare costs, and increased awareness. Challenges of depression screening include accuracy of screening tools, follow-up and treatment access, stigma and fear of diagnosis, and potential for overdiagnosis and overtreatment.

Behavioral health screening and counseling can be integrated into medical care facilities (e.g., women's health). Clinics are limited in how many patients can receive behavioral health services. There are significant disparities that prevent patients from receiving evidence-based behavioral health screening and counseling at the right time and place. The EQUIDEM data visualization project will allow healthcare teams to identify and serve patients who will benefit the most from limited behavioral health services.

Current Performance Monitoring. Currently, Valleywise Health (VH) screens all patients for depression symptoms. In 2023, the VH women's health clinic improved their UDS depression care performance (CMS2v11) from 48.25% to 73.44%, exceeding the national average of 70.02%. The monthly performance scorecard stratifies aggregated depression care data by age, gender, race/ethnicity, and geographical location. A quality assurance specialist uses SBAR to communicate and document improvement efforts. We expanded and enhanced the current universal screening and performance monitoring approach for depression care at VH by adding new monthly performance metrics, identifying key target patient groups, measuring service penetration disparities across target groups, developing a new Daily Huddle Report (addressing disparities in real time), soliciting staff input on the tools and root causes of depression care disparities, testing the enhanced data visualization using synthetic patient data. EQUIDEM is based on the rationale of an innovative combined universal screening and targeted intervention approach for pregnant and parenting women at risk for depression.

Implementation

Overview. This project was conceived as a comprehensive initiative to serve as a safety net for an at-risk patient population within the VH's integrated women's clinic. The EQUIDEM project builds on the success of existing care initiatives at VH, where universal screening at one campus has led to heightened awareness of patient wellbeing. The clinic provides both medical and behavioral services, ensuring integrated care management with social workers to address the complex needs of the patient base. In alignment with USPSTF recommendations, the project aimed to enhance depression care by developing advanced visualization tools to aid clinicians and staff in the identification and prioritization of those patients most in need of timely intervention.

Implementation Approach. To ensure a structured approach to the development and implementation of these visualizations the project was guided by the Plan-Do-Study-Act (PDSA) cycle. The PDSA cycle began with a detailed planning phase in which the full scope of the project's needs were delineated. This phase involved internal meetings between the data teams at VH and ASU, where the teams collaborated to identify the relevant depression care data necessary for building effective visualizations. These discussions also included consultations with the VH analysts to determine the most effective means of extracting the required data given constraints on data use agreements.

Tool Development. Both teams worked to design a SQL query specific to Epic Clarity data tables used by Valleywise Health. To validate the query, we used a large language model (LLM; ChatGPT 4.0) to review the list of clinical data variables and query code lines (see Tables 1 & 2; all tables in Appendix). The LLM recommended additional variables and specific coding appropriate for Epic Clarity. The ASU project leader and data analyst met three times with a VH Epic data analyst to review project scope, data variables, and query. After generating input and approving the final SQL query, VH analysts stood by to transfer the requested dataset to a virtual machine for testing. As of this report, the data transfer was not complete.

Focus Group Data. To solicit input on user-centered visualization and root causes of depression care disparities, a focus group study was conducted with clinical staff at VH. This focus group played a crucial role to ensure that the visualizations were developed utilizing user-centered design and aligned with the clinical workflow. The feedback gathered from these sessions were utilized to implement the dashboard visualizations utilizing synthetic data due to the inability to acquire the data with the timeframe initially anticipated. The synthetic data were designed to simulate real-world conditions, reflecting the patient demographics and clinical patterns typical of the VH system area. We created 125,000 rows of synthetic patient data using a Python script generated by ChatGPT. Using baselines of demographic-specific patient proportions and screening penetration rates, we estimated screening rates for target patient groups.

The final implementation phase concentrated on developing key dashboard visualizations to demonstrate the potential impact of the project. These visualizations served as a proof of concept, showcasing how near real-time data can be leveraged to improve patient care. By focusing on critical metrics—such as penetration rates for depression screenings across target groups like pregnant women, minorities, and those with a history of depression—the dashboards can provide healthcare providers with actionable insights. Although provider feedback has not yet been incorporated, gathering insights from them remains a future endeavor to further refine and optimize the dashboards for practical use in clinical settings.

Evaluation

Development and Implementation of Tools. We designed EQUIDEM to accomplish the following objectives: 1) increase completed depression screening and counseling rates for pregnant and postpartum women; 2) decrease wait times for completed depression counseling; 3) reduce service disparities by target patient groups in depression care. EQUIDEM includes two data visualization tools: 1) daily huddle report; 2) monthly performance scorecard. This design improves upon the previous data visualization using an automated process, adding six new performance metrics, supporting real-time clinical decision making, and integrating user-centered visualization elements (see Figure 1).

Our team did not advance to the full pilot phase of this project. The original goal was to use real, de-identified patient data to demonstrate the feasibility and utility of the two data visualization tools (daily huddle report; monthly performance scorecard). There were delays in the process to execute a data use agreement between VH and ASU and the in the process for the ASU Institutional Review Board to review the study protocol.

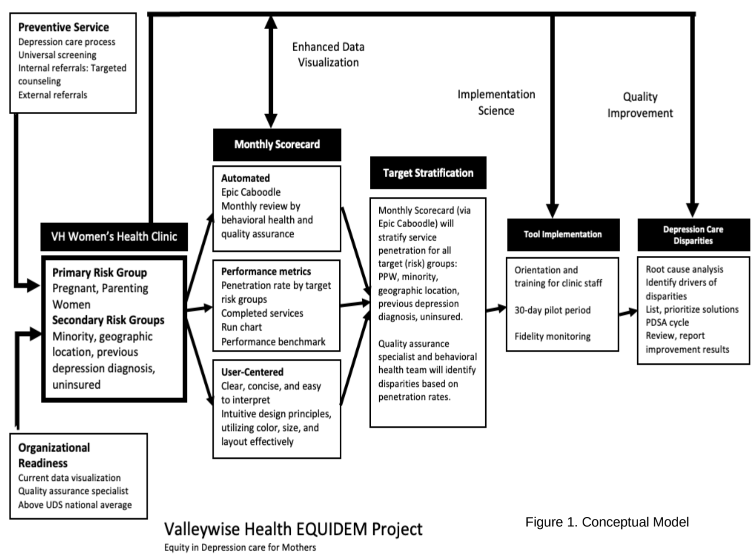


Figure 1. Conceptual Model

The ASU team successfully tested different variations of the tools in Tableau using synthetic patient data. In addition, we successfully collected user input from the women's health clinic team using a focus group method.

The focus group procedure with Valleywise clinical staff played a crucial role in the iterative design and enhancement of visualizations for their monthly metric scorecards and huddle reports. Initially, staff were presented with prototype visualizations and were asked to provide detailed feedback on clarity, intuitiveness, and the ability to effectively communicate trends, patterns, and outliers. This feedback was collected through structured discussions and usability testing sessions, where clinicians interacted with the visuals in realistic scenarios. The design team used this input to refine the visualizations, ensuring they were clear, easily comprehensible, and compatible with assistive technologies. This user-centered approach aimed to improve the administration of depression treatment by equipping clinic staff with practical insights and effective tools and training.

The design of user-centered visualizations for enhancing depression care management was driven by key themes identified through focus group discussions with clinic staff. Staff reported significant challenges with the current tools, particularly their inability to provide a comprehensive overview of patient data, which hindered efficient decision-making during evaluations. They emphasized the need for clear, easily understandable visualizations that could integrate critical metrics, such as patient demographics, screening results, and referral delays, into a unified and accessible dashboard. The importance of tracking monthly metrics to assess the effectiveness of depression screening and referral processes was also highlighted, ensuring optimized patient care pathways. Furthermore, the analysis of variations in PPD severity, as measured by PHQ-9 scores across different ethnic, racial, and geographical populations, underscored the need for tailored and equitable mental health interventions. These insights were instrumental in shaping visualizations that not only improve clinic workflows and patient management efficiency but also address significant disparities in depression care.

Identification and Response to Inequities. Here we review figures and insight developed from the analysis of synthetic patient data and the focus group findings. Figure 2 shows the first variation of the daily huddle report with vertical bars displaying the number of scheduled appointments with patients representing specific target groups. The far right patient schedule shows the patient names organized by provider name with corresponding depression screening status. The bottom table shows a similar schedule organized by provider name but with risk level and target group information. These figures were presented during the clinic focus group.

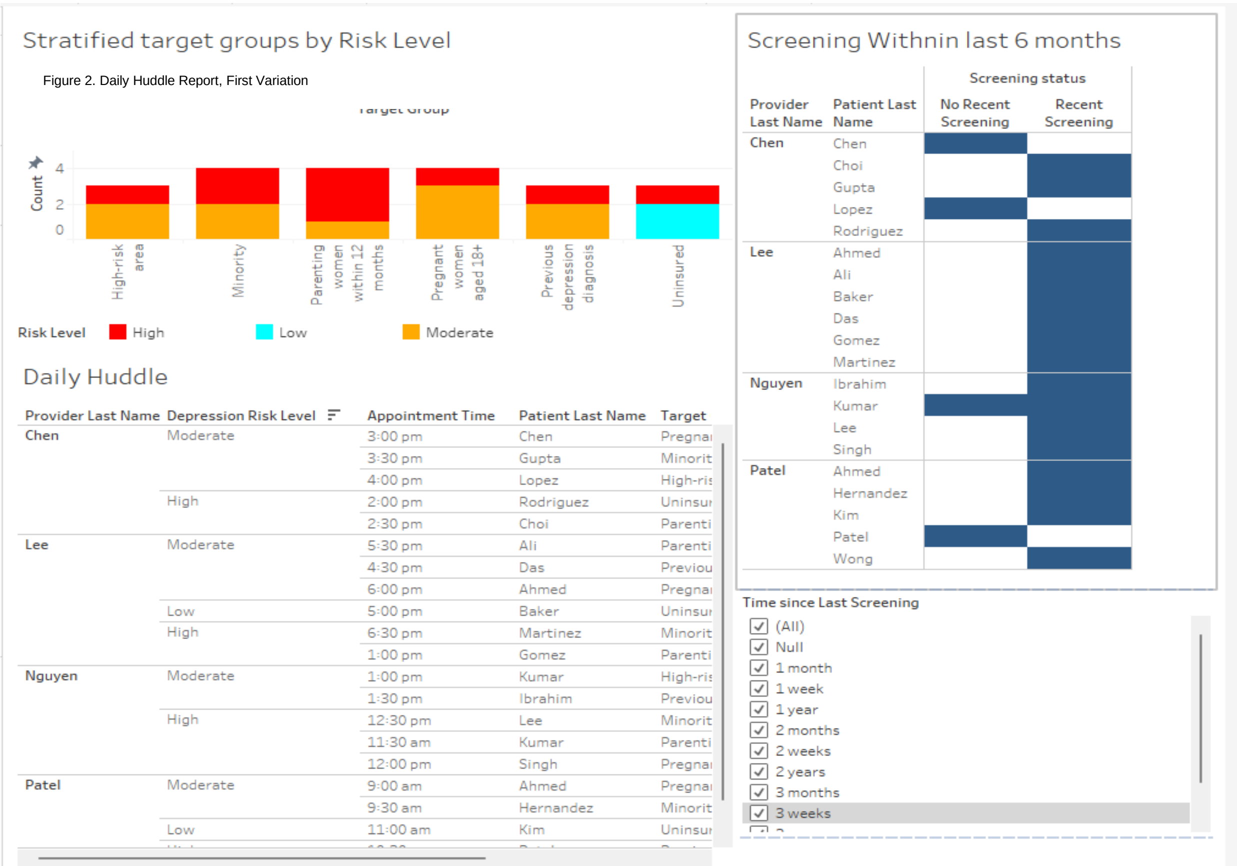


Figure 2. Daily Huddle Report, First Variation

Figure 3 shows a streamlined daily huddle report with ethnicity and race, screening scores, and color coded risk level. Clinic staff preferred a simple huddle report with a clear risk level and corresponding legend.

Daily Huddle Report

Figure 3

Appointment Date	MRN number	Ethnicity	Race	Pregnancy Test	Clinician ..	Zip Code	GAD-7 score	PHQ-9 score
4/6/2024	685	Hispanic/Latino	Other Pacific Islander	Positive	Harris	85041	5	27
4/2/2024	787	Non-Hispanic	American Indian	Positive	White	85009	1	25
4/16/2024	990	Hispanic/Non-Latino	American Indian	Positive	Thompson	85204	2	19
4/5/2024	431	Hispanic/Latino	Native Hawaiian	Positive	Jackson	85041	5	19
4/1/2024	160	Hispanic/Latino	Asian	Positive	Jackson	85323	11	19
4/14/2024	853	Hispanic/Non-Latino	White	Positive	Jackson	85225	17	17
4/7/2024	293	Hispanic/Latino	White	Positive	Harris	85035	8	17
4/15/2024	346	Hispanic/Non-Latino	American Indian	Positive	Jackson	85225	11	16
4/4/2024	604	Hispanic/Latino	Native Hawaiian	Positive	Jackson	85041	4	15
4/13/2024	598	Non-Hispanic	Alaska Native	Positive	White	85225	12	13
4/3/2024	364	Non-Hispanic	American Indian	Positive	Jackson	85225	13	12
3/31/2024	676	Non-Hispanic	Native Hawaiian	Positive	Harris	85323	20	12
4/17/2024	416	Hispanic/Non-Latino	White	Positive	Thompson	85040	13	5
4/11/2024	542	Hispanic/Non-Latino	American Indian	Positive	White	85042	4	5
4/10/2024	865	Hispanic/Non-Latino	Other Pacific Islander	Positive	White	85042	19	5
4/19/2024	612	Hispanic/Non-Latino	Native Hawaiian	Positive	Jackson	85204	20	3
4/9/2024	208	Hispanic/Non-Latino	Other Pacific Islander	Positive	Harris	85042	6	3
4/18/2024	699	Non-Hispanic	Asian	Positive	White	85204	15	2
4/12/2024	119	Hispanic/Non-Latino	White	Positive	White	85225	9	2
4/8/2024	460	Hispanic/Latino	Alaska Native	Positive	Harris	85042	7	2

PHQ-9 Score Range (color) broken down by Appointment Date, sum of MRN number, Ethnicity, Race, Pregnancy Test, Clinician Last Name, Zip Code, sum of GAD-7 score and sum of PHQ-9 score. The data is filtered on Appointment Date, which ranges from 3/31/2024 to 4/19/2024.

PHQ-9 Score Range
- 1. Minimal depression (score 1-4)
- 2. Mild depression (score 5-9)
- 3. Moderate depression (score 10-14)
- 4. Moderately severe depression (score 15-19)
- 5. Severe depression (score 20-27)

Figure 4 shows a similar report but with new columns indicating pregnancy status and completion of previous referrals and counseling services. Staff want information on previous services, but still prefer a simpler color coded report with clear recommendations for next steps.

Clinician View II (PHQ-9 Score)

Figure 4

Referral ..	Pregnancy Test	Internal counseling completion	Internal Referral Completion	External Referral Completion	PHQ-9 score
4443	Positive	4/19/2024	null	5/2/2024	25
4457	Positive	4/23/2024	null	5/27/2024	19
4446	Positive	5/3/2024	null	5/21/2024	19
4442	Positive	4/19/2024	null	5/16/2024	19
4455	Positive	5/7/2024	null	5/23/2024	17
4440	Positive	4/20/2024	null	5/15/2024	17
4456	Positive	5/14/2024	null	5/26/2024	16
4445	Positive	4/23/2024	null	5/10/2024	15
4432	Positive	4/19/2024	null	5/22/2024	15
4454	Positive	5/11/2024	5/31/2024	null	13
4441	Positive	4/24/2024	4/26/2024	null	12
4458	Positive	4/21/2024	5/6/2024	null	5
4452	Positive	5/4/2024	5/8/2024	null	5
4451	Positive	4/21/2024	5/11/2024	null	5
4460	Positive	5/17/2024	null	null	3
4459	Positive	4/19/2024	null	null	2
4453	Positive	5/8/2024	null	null	2
4449	Positive	5/6/2024	null	null	2
4438	Positive	4/27/2024	null	null	2

PHQ-9 Score Range (color) broken down by Referral Number, Pregnancy Test, Internal counseling completion, Internal Referral Completion, External Referral Completion and sum of PHQ-9 score. The data is filtered on Internal counseling completion, which includes dates on or after 4/18/2024.

PHQ-9 Score Range
- 1. Minimal depression (score 1-4)
- 2. Mild depression (score 5-9)
- 3. Moderate depression (score 10-14)
- 4. Moderately severe depression (score 15-19)
- 5. Severe depression (score 20-27)

Figure 5 reveals an early variation of the monthly performance scorecard. The top run chart displays performance over time across six target patient groups (e.g., ZIP code, depression history, minority, PPW, uninsured). The lower vertical bar graph displays the penetration rates for each target group. The scorecard (Figures 5-7) is based on synthetic patient data we created using a Python script generated by ChatGPT. Using baselines of demographic-specific patient proportions and screening penetration rates, we estimated screening rates for target patient groups.

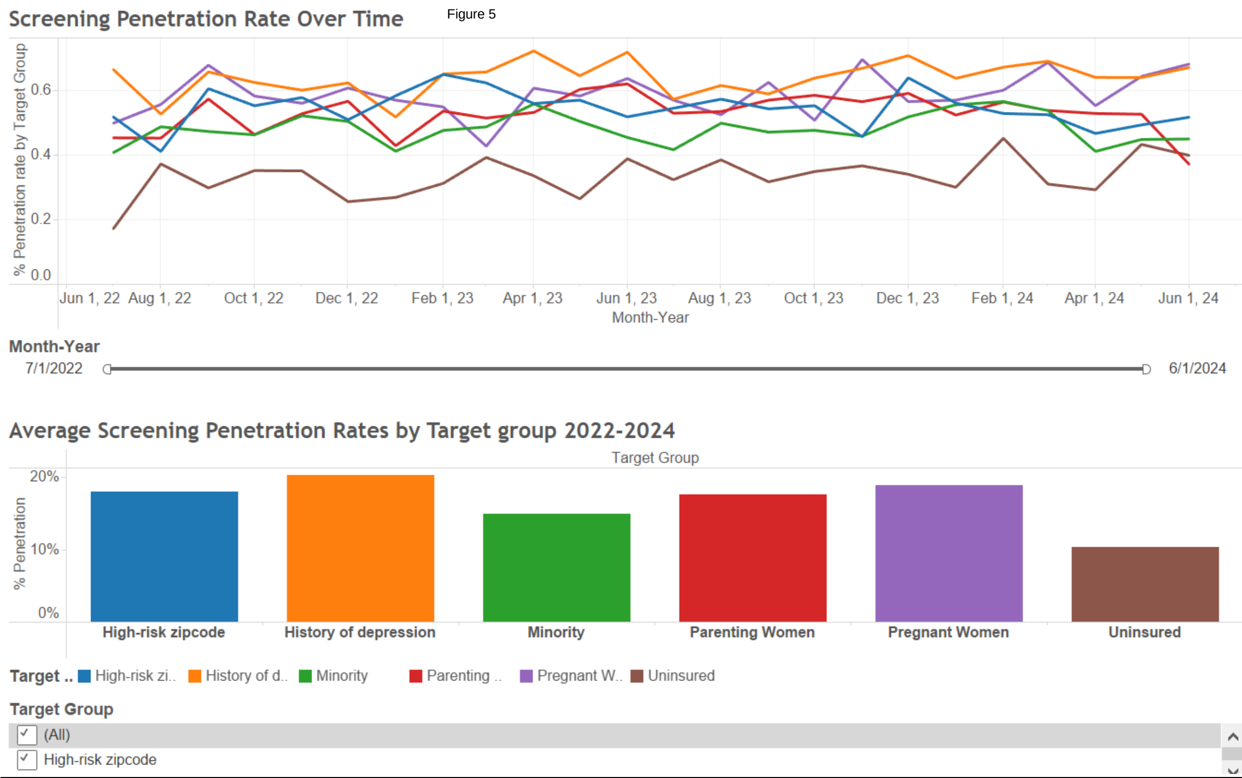


Figure 6 shows a visualization of depression care referral completion rate over time, organized by target group.

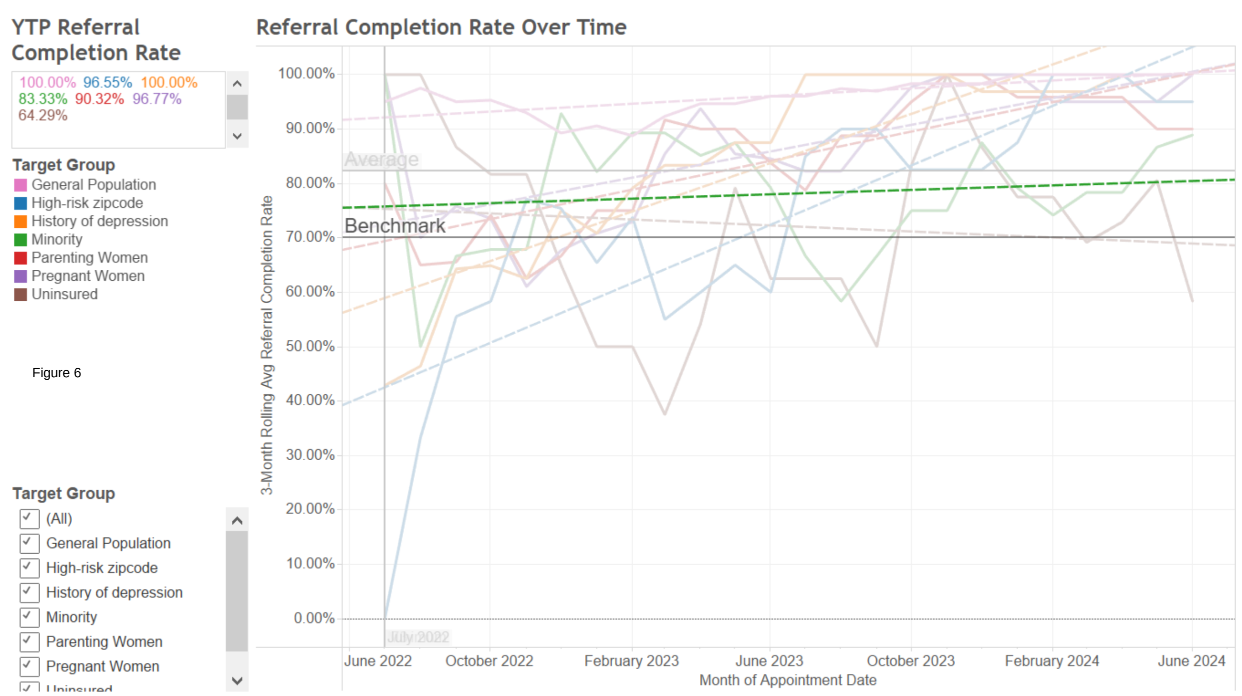
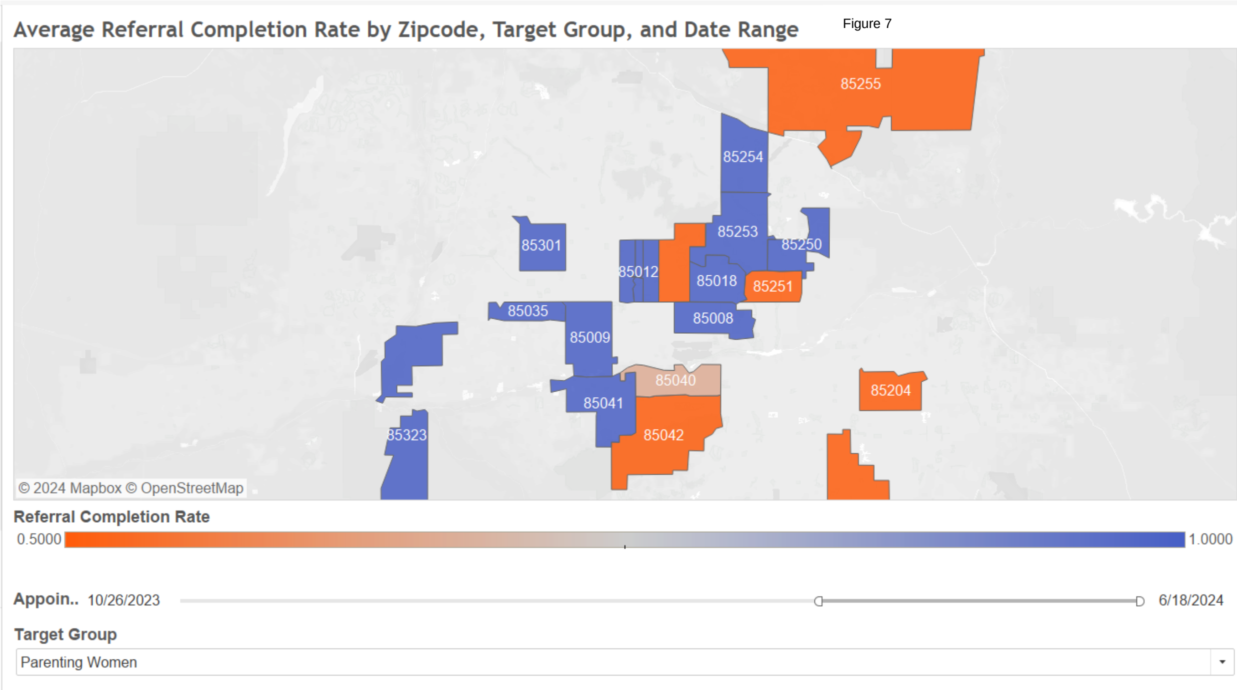


Figure 7 shows visualizes referral completion rates for selected target group 'Parenting Women' across different zip codes over time.



During the focus group, clinical staff reported a universal screening approach for all patients in the women's health clinic. However, they stated referral and follow-up rates are not 100% for several reasons. First, patients face barriers such as transportation issues, financial constraints, or stigma associated with mental health care, making it difficult for them to follow through on referrals. Second, systemic issues, such as delays in referral processes, long wait times for mental health services, or limited availability of social services, can hinder timely follow-up. Third, if patients are not actively engaged in their care plans, they may be less likely to follow through with referrals or attend follow-up appointments. This can make it challenging for staff to ensure that follow-up care is completed. Last, staff sometimes have multiple competing priorities, including managing acute medical needs, which can overshadow the importance of following up on depression care referrals (this is the least likely scenario). Staff report that a valid and reliable data visualization tool (i.e., monthly performance scorecard) would enhance their follow-up efforts of target patient groups.

Lessons Learned. There are three lessons learned from this pilot project. First, the clinic team members recognize the value of improving depression care performance and monitoring individuals at risk for untreated mental health needs. The medical director revealed that the clinic is participating in an incentive program to improve identification and care of women living with anxiety. The director wondered if the proposed data visualization tools could be modified for other behavioral health and social needs (e.g., anxiety, housing, substance use). Our findings indicate that there is strong support for expanding data visualization capacity. Second, clinicians and staff want simple huddle reports that support accurate identification of at-risk patients, quick treatment planning, and seamless integration into clinical workflow. They also want monthly performance scorecards that are easy to interpret and translate into clear quality improvement opportunities. Third, we learned that large language models (e.g., OpenAI ChatGPT) are useful for designing and refining data visualization tools that require SQL queries, alignment with Epic data tables, and user-centered design. ChatGPT output positively correlated with feedback from the VH Epic analysts and the clinic care team. Future pilot projects can benefit from integrating ChatGPT at different project phases.

Future Plans

Valleywise Health and ASU will continue this program of research. Our team is actively working toward demonstrating the new data visualization tools using real, de-identified patient data. Unfortunately, the required authorizations did not come through in time to demonstrate the tools for this final report. We anticipate using real patient data within the next 1-2 months. The following sections list our recommendations for sustaining a data pipeline that supports daily and monthly data visualization tools and our plans for a specific implementation project and eventual dissemination efforts.

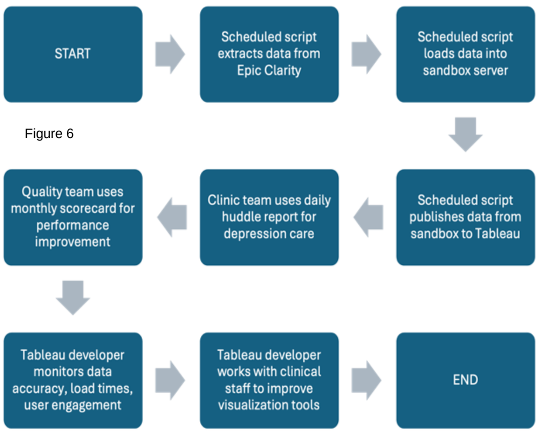


Figure 6

Sustainability Plan. Based on projects results, we designed a process that establishes a data pipeline between the electronic health record system and the data visualization platform and supports the efforts of clinical and quality improvement staff (see Figure 6). This process uses scheduled scripts that automatically transfer data from the electronic health record system into a temporary sandbox server and then into a data visualization platform (e.g., Tableau). A separate scheduled script transfers daily data to populate the huddle report and another script transfers monthly data for the performance scorecard. A dedicated Tableau developer monitors the data pipeline for accuracy, load times, and user engagement. The developer works directly with clinical staff to review and improve the tools.

Sustaining the new data pipeline will require continuous improvement and effective control strategies. The Tableau developer can set up real-time alert systems (e.g., email, SMS) for any pipeline failures or performance degradation. This allows for immediate response and minimizes downtime. They will also use Tableau's built-in performance recorder or third-party tools to monitor dashboard performance over time and regularly review these metrics to ensure that the dashboards remain responsive and efficient. A hospital executive will work with the Tableau developer to regularly gather feedback from the clinicians and other end-users to ensure the dashboards meet their needs and that the data provided are timely and accurate. This feedback should be incorporated into continuous improvement efforts. Control strategies like automation, regular audits and quality checks, change management procedures, and redundancy and failover mechanisms will ensure the data pipeline between Epic and Tableau operates efficiently, delivers high-quality data, and remains responsive to the needs of end-users.

In addition to continuous improvement, a cost-benefit analysis (CBA) can justify the ongoing costs and efforts required to maintain and improve a data visualization system for improved mental healthcare. We identified the costs and benefits of implementing the data pipeline (see Table 3). The CBA will calculate the net present value of the pipeline by comparing the total discounted benefits to the total discounted costs. A positive value indicates that the benefits outweigh the costs. The CBA can inform decisions about resource allocation, help in planning for long-term sustainability, and provide financial justification for ongoing investment in the pipeline.

Implementation Measures and Strategies. This pilot project partially demonstrated the feasibility and utility of data visualization tools for improved depression care in a women's health clinic. Our findings suggest that a data pipeline is feasible and that clinic staff value tools that support more timely and equitable patient care. The next step is to conduct an implementation study using a Type 2 hybrid research design measuring effectiveness and adoption of the data visualization tools (see Table 4). Using the RE-AIM model, we identified measures appropriate for evaluating the implementation study (see Table 5).

The results of the implementation study can support spread of the tools across the Valleywise Health system and contribute to the scientific literature. The study should take place within the women's health clinic where employees are primed for practice enhancement.

The implementation study will require external funding. We identified two funding mechanisms appropriate for this research program. First is a R21/R33 phased innovation award from AHRQ (*Using Innovative Digital Healthcare Solutions to Improve Quality at the Point of Care, PA-24-266*) that provides 2-3 years of funding support. Second is a R01 clinical trial award from NIH (*Leveraging Health Information Technology (Health IT) to Address and Reduce Health Care Disparities, PAR-22-145*) that provides up to 5 years of funding support. It appears that both funding opportunities are appropriate for our implementation study proposal.

Plan for Spread. Valleywise Health leaders are motivated to continue this program. The women's health clinic is currently participating in a state-wide financial incentive program to better identify and address anxiety. During the focus group, clinic staff reported a desire to develop data visualization tools for a variety of mental health and social need services. We identified other metrics related to improved healthcare outcomes and equity for pregnant and parenting women (see Table 6).

Dissemination, or spread, requires careful planning. By following a comprehensive plan, Valleywise Health can effectively spread the use of data visualization tools across other clinics, ensuring that the benefits observed in the women's health clinic are realized more broadly across the organization. We developed a ten step plan (see Table 7).

Appendix

Table 1. Raw Data Variables for Daily Pull		
Variables	**Conditions/Requirements**	**Formatting**
Provider name	Name of provider	Formatted as string: two separate variables for Last, First
Patient ID/Number	Unique identification number used for de-identification	String
Appointment date	All appointments scheduled for current date that are for people who are a member of at least one target group	formatted date as mm/dd/yyyy
Appointment time	Exact time of appointment	formatted time as hh:mm am/pm
Age	Age of patient	Formatted as number from age attribute of database
Target group	Target group patient is in (must be at least one of the following but can be more than one which should be documented as a string list): Pregnant women aged 18+. Parenting women who have given birth within 12 months from today's date. Minority: American Indian/Alaska Native, black/African American, Hispanic. Geographical location is one of the following zipcodes: 85323', '85301', '85035', '85009', '85041', '85008', '85204', '85040', '85225', '85042 Previous depression diagnosis in medical history: ICD10 coder between F30 and F49 or if mental status is depressed Uninsured: if financial class is one of the following: 'Self-Pay', 'Received Self-Pay', 'Sent to Consolidated Self-Pay Service Area'	string or list of strings that list the target group the patient is a member of
Depression History date	Previous depression diagnoses/problems from any previous encounter for any patient.	Show as mm/dd/yyyy, or if null, list Null
Last Depression screening date	Date of last screening.	Formatted as mm/dd/yyyy, or if nothing known null
Internal referral date	If any previous screen is positive for depression, list referral date,	formatting: date as mm/dd/yyyy, if no previous diagnoses list NA, list Null
external referral date	If any previous screen is positive for depression, list referral date,	formatting: date as mm/dd/yyyy, if none, list Null

Table 2. Raw Data Variables for Monthly Performance Scorecard*		
Variable	**Description/requirements**	**Formatting**
Patient identification number	Number	Int
Appointment date	All appointments scheduled for current date that are for people who are a member of at least one target group	Formatted date as mm/dd/yyyy
Gender	Binary category	String
Zip code	Five digit number representing ZIP code	Number
Race	Category of race that is all inclusive of types: American Indian or Alaska Native, Black or African American, Other Asian, Other Pacific Islander, White, Refuse to answer, Unknown, other combined (Chinese, Korean, Asian Indian, Vietnamese, Filipino)	String
Ethnicity	Category of ethnicity that is all inclusive of types: Mexican American, Chicano, Non-Hispanic Latino/a, Spanish, Refuse, Unknown, Other Hispanic, Cuban, Puerto Rican, Non-Hispanic/Non-Latino/a	String
Age	Age of patient	Formatted as number from age attribute of database
Target group	Target group patient is in (must be at least one of the following but can be more than one which should be documented as a string list: Pregnant women aged 18+. Parenting women who have given birth within 12 months from today's date. Minority: American Indian/Alaska Native, black/African American, Hispanic Geographical location is one of the following zipcodes: 85323', '85301', '85035', '85009', '85041', '85008', '85204', '85040', '85225', '85042 Previous depression diagnosis in medical history: ICD10 coder between F30 and F49 or if mental status is depressed Uninsured: if financial class is one of the following: 'Self-Pay', 'Received Self-Pay', 'Sent to Consolidated Self-Pay Service Area'	String or list of strings that list the target group of patients
Depression diagnosis date	Previous depression diagnoses from any previous encounter for any patient	Show as mm/dd/yyyy, or if null, list Null

Last Depression screening date	Date of last screening	Formatted as mm/dd/yyyy, or if nothing known null
Internal referral date	If any previous screen is positive for depression, list referral date	Formatting: date as mm/dd/yyyy, if no referral list Null
Internal counseling complete	Date of first counseling session following referral date	Formatting: date as mm/dd/yyyy, if no previous diagnoses list na, list null
External referral date	If any previous screen is positive for depression, list referral date	Formatting: date as mm/dd/yyyy, if none, list null
* Monthly data to pull from Epic for all patients in the target groups for all encounters for the previous two calendar years, the first month starting in January.		

Table 3. Cost Benefit Analysis of Data Pipeline	
Costs	**Benefits**
<u>Initial Setup Costs</u>: purchase of software licenses (e.g., Tableau), hardware, development hours, and consulting fees. Costs associated with configuring Epic Clarity, setting up the sandbox server, and integrating with Tableau. Tableau developer compensation.	**<u>Improved Decision-Making</u>**: improvement in decision-making quality due to timely and accurate data visualization in Tableau. Improved patient outcomes and health equity, more efficient resource allocation, and ultimately, better overall healthcare delivery.
<u>Ongoing Operational Costs</u>: maintaining the pipeline, such as data storage, server maintenance, Tableau Server licensing, ongoing development, monitoring, and potential scalability needs. Cost of training staff to use and manage the pipeline effectively. Tableau developer compensation.	**<u>Operational Efficiency</u>**: reduces the time and effort required for manual data extraction, transformation, and reporting. Clinicians and data analysts can focus on more strategic tasks, leading to productivity gains.
<u>Unexpected Costs</u>: a buffer for unexpected costs, such as troubleshooting, emergency fixes, or significant upgrades needed to keep the system efficient and secure.	**<u>Cost Savings</u>**: reduce labor costs and minimize errors that could lead to costly rework or compliance issues. Prevent downstream problems, such as incorrect patient treatments or inefficient use of resources.
	<u>Scalability and Flexibility</u>: as Valleywise Health expands or the volume of data increases, the system can adapt without requiring a complete overhaul, thereby saving future costs.

	<u>Support for Strategic Goals</u>: provide insights into patient mental healthcare contributing to broader strategic goals, such as improving patient outcomes and health equity, achieving value-based care targets, and enhancing overall healthcare quality.

Table 4. Implementation Study Aims and Research Questions

Study Aims	Research Questions
1. Evaluate the Effectiveness of the Data Visualization Tools in Improving Depression Care Outcomes	1.1: How does the implementation of the data visualization tool impact key depression care outcomes, such as screening rates, treatment initiation, and follow-up adherence within the women's health clinic? 1.2: What changes in patient outcomes (e.g., PHQ-9 score improvements, patient satisfaction) are observed after the adoption of the data visualization tools? 1.3: Are there differences in the effectiveness of the data visualization tools among different patient subgroups (e.g., by age, race / ethnicity, socioeconomic status)?
2. Assess the Adoption and Utilization of the Data Visualization Tools by Clinic Staff	2.1: What proportion of clinic staff regularly use the data visualization tools in their daily workflow? 2.2: What are the barriers and facilitators to the adoption of the data visualization tools among clinic staff? 2.3: How does the use of the data visualization tools influence clinical decision-making and care coordination practices?
3. Evaluate the Implementation Process and Identify Factors Influencing the Successful Integration of the Tools	3.1: What are the key implementation strategies used to integrate the data visualization tools into the clinic's workflow? 3.2: How do organizational factors (e.g., leadership support, resource availability, clinic culture) impact the implementation process? 3.3: What adaptations, if any, are made to the data visualization tools or the implementation process to fit the specific context of the women's health clinic?

Table 5. Implementation Measures

Measures*	Definition
<u>Reach</u> 1.1: Patient Demographics Reached 1.2: Patient Engagement	1.1.2: Percentage of eligible patient population that was screened for depression using data visualization. 1.1.2: Demographic characteristics of patients who were reached versus those who were not. 1.2.1: Number and percentage of patients who, after being identified through data

	visualization, engaged in follow-up care or treatment for depression. 1.2.2: Patient feedback on accessibility and clarity of information provided through data visualization.
Effectiveness 2.1: Depression Care Outcomes 2.2: Patient Satisfaction and Experience 2.3: Clinical Decision-Making	2.1.1: Changes in key depression care metrics, screening rates, treatment initiation rates, and follow-up adherence before and after implementation of data visualization tools. 2.1.2: Percentage of patients with improved depression outcomes (e.g., reduction in PHQ-9 scores) after the adoption of the tools. 2.2.1: Patient satisfaction with care received as influenced using data visualization. 2.2.2: Patient-reported outcomes related to understanding and involvement in their care. 2.3.1: Qualitative and quantitative assessment of how data visualization influenced clinical decision-making (e.g., changes in treatment plans, referral rates).
Adoption 3.1: Clinic Staff Utilization 3.2: Barriers and Facilitators to Adoption 3.3: Training and Competence	3.1.1: Percentage of clinic staff who regularly use data visualization in their workflow. 3.1.2: Frequency and consistency of use across different staff roles. 3.2.1: Survey or interview data identifying barriers (e.g., technical difficulties, time constraints) and facilitators (e.g., ease of use, perceived usefulness) to adoption of tools. 3.2.2: Proportion of staff who report data visualization as being useful and easy to integrate into daily routines. 3.3.1: Number of staff trained to use data visualization. 3.3.2: Staff competence in using tools, measured by post-training assessments or surveys.
Implementation 4.1: Fidelity to Implementation Protocol 4.2: Organizational Support 4.3: Resource Utilization	4.1.1: Degree to which data visualization tools were implemented as intended, including adherence to planned training, integration processes, and usage protocols. 4.1.2: Assessment of any deviations from planned implementation process and their impact on outcomes. 4.2.1: Level of organizational support, including leadership engagement, resource allocation, and technical support for implementation of data visualization. 4.2.2: Availability and use of technical assistance to address issues encountered during implementation. 4.3.1: Time and resources spent on implementing and maintaining data visualization, including training time, IT support, and data management. 4.3.2: Costs associated with implementation, including software, hardware, and personnel costs.
Maintenance 5.1: Sustainability of Tool Usage 5.2: Long-Term Outcomes 5.3: Organizational Integration	5.1.1: Long-term usage rates of data visualization tools by clinic staff after initial implementation period. 5.1.2: Changes in tool usage over time and factors influencing continued use or abandonment. 5.2.1: Sustained improvements in depression care outcomes (e.g., sustained reduction in PHQ-9 scores) over a longer period, such as 6 months or 1 year after implementation. 5.2.2: Ongoing patient engagement and satisfaction with depression care after

	initial implementation phase. 5.3.1: Extent to which data visualization has become embedded in the clinic's standard operating procedures. 5.3.2: Integration of the tools into other clinic processes or expansion to other areas of care beyond depression.
* RE-AIM model is an implementation research framework to evaluate health interventions.	

Table 6. Other Performance Metrics Appropriate for Data Visualization	
Mental Healthcare Follow-Up	Rate of mental healthcare referrals within the recommended timeframe (e.g., within 2 weeks after referral).
Prenatal Care Utilization	Percentage of pregnant women receiving timely prenatal care visits, including early and consistent care throughout pregnancy.
Postpartum Care Follow-Up	Rate of postpartum care visits within the recommended timeframe (e.g., within 6 weeks after delivery).
Gestational Diabetes Screening	Percentage of pregnant women screened for gestational diabetes, along with follow-up and management rates.
Diabetes Management	Percentage of women with diabetes who achieve target HbA1c levels, including monitoring of complications and adherence to care plans.
Access to Care	Percentage of women reporting barriers to accessing healthcare services, including transportation, cost, or lack of insurance.
Food and Housing Insecurity	Rates of food and housing insecurity screening among women, including follow-up on nutrition support and counseling and housing referrals.

Table 7. 10-Step Plan for Disseminating Data Visualization Tools
1. Develop a Strategic Dissemination Framework Define Goals and Objectives Identify Target Clinics
2. Customize the Implementation Approach Conduct Needs Assessments Tailor the Tools and Process
3. Engage Stakeholders Identify and Involve Key Stakeholders Build a Network of Champions
4. Provide Training and Technical Assistance Develop Comprehensive Training Programs Offer Ongoing Technical Support
5. Establish a Standardized Implementation Process Create an Implementation Guide Pilot in Selected Clinics

<u>6. Monitor and Evaluate Progress</u> Set Up Monitoring Systems Conduct Regular Check-Ins
<u>7. Foster a Learning Community</u> Create a Collaborative Network Encourage Continuous Improvement
<u>8. Communicate Success and Value</u> Share Success Stories Engage Senior Leadership
<u>9. Scale and Sustain</u> Plan for Scalability Sustainability Planning
<u>10. Evaluate System-Wide Impact</u> Conduct a System-Wide Evaluation Report Findings and Adjust Strategy