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Evaluating the Impact of a No-show Policy: A Quality Improvement Project

Adrianne S. Harding

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Adrianne S. Harding BSN, RN

A DNP project submitted in partial fulfillment of the requirements for

the degree of Doctor of Nursing Practice, Davis & Henley College of Nursing

Dr. Constance Glenn DNP, MSN, FNP-BC, CNE; DNP Project Faulty Advisor

Janice Tavares APRN FNP-BC; Practice Mentor

Sacred Heart University Davis & Henley College of Nursing

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This is to certify that the DNP Project Final Report by

Adrianne S. Harding

has been approved by the DNP Project Team on

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DNP Project Faculty Advisor: Dr. Constance Glenn DNP, MSN, FNP-BC, CNE

Practice Mentor: Janice Tavares APRN FNP-BC

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Abstract

Significance and Background: No- shows are a global problem that creates a significant challenge for the healthcare system. When a patient misses an appointment, it decreases health care staff productivity, creates a waste of resources and it negatively impacts revenue (Lance et. al, 2021). Current evidence supports interventions that incorporate voluminous data and artificial intelligence with strategies such as overbooking, appointment notification systems and financial incentives to reduce outpatient no-shows (Oikonomidi et al., 2022). This project will evaluate the impact of a no-show policy and provide insights to improve primary care attendance and inform decisions.

Purpose: To evaluate an outpatient primary care office adherence to a no-show policy and its impact on practice revenue based on current evidence.

Methods: Plan-Do-Study-Act. Plan- No- show and demographic attributes from March 2022 to February 2023 were discussed. Do- No- show data from March 2022 to February 2023 was collected from the electronic health record. Study- No-show data was analyzed. Act- Present to stakeholders and plan for next PDSA cycle.

Outcome: During a 12-month period, the primary care practice reported 1435 (17%) no-show occurrences, in comparison to the national average no show rate of 18%. The practice implemented a short message service (SMS) appointment notification system. There was a 38% decrease in the average monthly rate of no-shows in the 4 months post SMS implementation. With the United States national average cost of $218 for a primary care visit, a return on investment for SMS implementation was $11,554. Implications from the study suggest that no-show patients have greater than 10 chronic illness' and are missing follow- up visits. SMS implementation was shown to decrease the number of no-show appointments of patients with chronic illnesses and missed follow up appointments.

Discussion: Appointment reminders reduce no-shows. Artificial intelligence can optimize solutions to mitigate no-shows. Machine learning can be utilized to detect patterns in identifying appointments at high risk of no-show and guide practice decision making. Reducing no-show rates can decrease the cost on the healthcare system, improve resource efficiency and patient outcomes while decreasing loss of revenue.

Keywords: *No-shows rates, appointment notification, cost effectiveness, electronic health record, primary care.*

Problem Identification & Evidence Review

Background and Significance of Problem

A no-show is described as a patient who does not show up for their scheduled appointment without contacting the healthcare provider (Oikonomidi et al., 2022). No- shows are a global problem that creates a significant challenge for the healthcare system. In the United States, no shows cost the healthcare system more than $150 billion a year (Saif et al., 2018). Researchers estimate that the national annual average no-show rate is 18% (Kheirkhah et. al, 2016). When a patient misses an appointment, it decreases health care staff productivity, creates a waste of resources and negatively impacts revenue (Lance et. al, 2021). No-shows have a direct correlation with negative health outcomes and are an independent predictor for increased use of acute care and emergency department services. (Oikonomidi et al., 2022). When a patient misses an important screening or diagnostic testing, it places the individual at risk for delayed disease detection.

There is a consensus that outpatient no-shows are a complex, multifactual phenomenon directly related to patient characteristics. These include demographics relevant to equity, for example low-income families, transportation issues and health disparities. Other factors include characteristics of the appointment, such as lead time and the location of the healthcare system, where access to transportation can be an issue.

Current industry interventions incorporate the concept of voluminous data and artificial intelligence with strategies such as overbooking, appointment notification systems and financial incentives to reduce no-shows (Oikonomidi et al., 2022). Artificial intelligence can optimize solutions to mitigate no-shows. Predictive models and machine learning have been used to detect patterns in identifying appointments at high risk of no-show and guiding the selection of appointments to double-book. Reducing no-show rates can decrease the cost on the healthcare system and improve the quality of health care delivery (Kheirkhah et.al, 2016).

Description of Local Problem/Organizational Priority

A primary care and cardiology office located in the northeast United States, serves adults older than 18 with chronic illnesses from low-income households. In 2019, the practice reported seeing 16,657 patients with 526 no-show occurrences and 2980 cancellations, reflecting a 21% no-show rate. To decrease the no show rate, the practice implemented a no-show policy July 1, 2021 (Appendix E). In November 2022, the practice implemented a short message service (SMS) appointment reminder system, that sends patients reminders 3 days prior to their appointment. This project has the support of the Chief Executive Officer (CEO) and practice manager and aims to evaluate the adherence to a no-show policy and its impact on revenue.

Focused Search Question

In out-patient primary care (P), does the adherence to a no- show policy (I) compared to non-adherence (C) impact revenue (O) over a 12-month period (T)?

Evidence Review

External Evidence. Databases searched include CINAHL Complete, MEDLINE full text with key words: no-show rates, missed appointments, cancellation, appointment notification, cost effectiveness, electronic health record. Searches of peer review articles published in English between 2016 – 2022. Each research article was appraised using the level of evidence (LOE) hierarchy (Melnyk & Fineout-Overholt, 2019). The final yield from all databases was a total of eight articles (Appendix B).

Internal Evidence. The practice has since made subsequent changes to the no show policy, to include short message service (SMS) notification system. Preliminary data from the practice suggests the need for best practices to evaluate the impact of a no-show policy in primary care.

Evidence Appraisal, Summary, and Recommendations

Eight articles were critically appraised for level of evidence (LOE) (Appendix C). The key outcomes of each article were delineated for comparison in a synthesis table (Appendix D). Out of the eight articles, article one was LOE I, article two was LOE I, article three was LOE II, article four was LOE I, article five was LOE II, and article six was LOE IV, article seven was a LOE IV, article eight was LOE III.

As noted in the evaluation and synthesis tables, the no show rates decreased (articles one, two, three, and six) (see Appendices B, C and D).

An increasing number of organizations utilize Artificial Intelligence (AI) to reduce gaps in quality care by implementing the best evidence-based practice. SMS reminders have been used to facilitate behavior change through coaching and prompting to enhance prospective memory, such as remembering to complete an activity in the future (Schwebel & Larimer, 2018). SMS reminders are relatively inexpensive, easily custtomized, and are automatically sent. SMS reminders have been found to either increase the rate of appointment attendance, increase the rate of appointments cancelled ahead of time, or decrease the rate of missed appointments (Schwebel & Larimer, 2018). Robotham et al. (2016) found that patients who received text message reminders were 23% more likely to attend appointments compared to those who received no notification. When comparing SMS and telephone reminders, SMS notification is cheaper however, telephone reminders are more cost effective. Lance et. al, 2021 found that for each dollar invested in SMS, there was a return of $2.67 while the return on investment related to telephone calls was $15.24. The investment of $141,000 in telephone calls could avoid a loss of around $2.1 million per year. To avoid the high cost of sending reminder notifications to every patient, most studies suggest sending notifications to patients who are at high risk of no-show (Coley et. al, 2022; Salazar et. al, 2022; Robotham et.al, 2016).

Oikonomidi et al., 2022 and Salazar et. al, 2022 found that machine learning (ML) and predictive models using text message reminders, were effective in reducing no show rates. Coley et. al (2022) used risk prediction models in the EHR to send an additional text message reminder to patients with a high-risk of no shows and achieved higher efficiency at lower costs to the health system when compared to sending a message to all patients.

Various factors affect no-show, including age, gender, visit type, time of appointment (day and month), distance, and patient health status. (Kheirkhah, et. al, 2016). On average, 17 attributes based on the most influential factors that impact no shows are utilized to build predictive models (i.e. age, sex, zip code). Salazar et. al, (2022) found that prior to ML trained model the initial no show rate was (85%) and post ML trained models the no show rate decreased to 10%. Studies suggest that the smaller the data the more accurate the model will perform, using Gradient Boosting, Decision Trees, and Random Forest for the best performance (Salazar et. al, 2022).

Studies have reported major finacial savings after implementing an automated SMS reminder system, and attribute savings to the relative inexpensiveness and the decreased rate of missed appointments. (Schwebel & Larimer, 2018). Estimating the cost of an intervention can be challenging however, evaluating the cost of technology can provide insights into individual practice sites. Estimating cost can inform decisions like adopting similar strategies for another practice location (Wagner et. al, 2020).

Evidence-based AI development and deployment through quality improvement can address systemic issues in primary care and aid in standardizing AI practices in healthcare. The purpose of this quality improvement project is to evaluate a primary care practice adherence to a no-show policy and its impact on practice revenue based on current evidence.

Project Plan

Project Goals

1. Implement an evaluation to measure a primary care practice's adherence to a no-show policy.
2. Evaluate a primary care practice's annual no-show rate in comparison to the national annual average no-show rate of 18%.
3. Utilize business intelligence software (Microsoft Power BI) to analyze no show data between March 2022 to February 2023, from the electronic health record (EHR) and SMS notification system.
4. Evaluate the financial impact of a SMS notification system from July 2022 to October 2022 (Pre-SMS implementation) and November 2022 to February 2023 (Post- SMS implementation) to determine if there is a 20% increase in revenue post implementation.
5. Identify patient variables associated with primary care no-shows and provide recommendations.

Project Design and Methodology (EBP Process Steps 0-3)

Framework

The methodology for this project began with the evidence-based practice (EBP) process steps 0-3 (Melnyk & Fineout-Overholt, 2019) that revealed using artificial intelligence thorough SMS notification is effective in reducing no show rates. The framework used to guide this project is the Model for Improvement (MFI). MFI provides a framework for developing, testing, and implementing changes for improvement. The Plan-Do-Study-Act (PDSA) will guide the application of the MFI for this QI project. Appendix D outlines the steps for the PDSA cycle.

Plan Phase. The DNP student met with the primary care nurse practitioners and the office manager to discuss the practice adherence to a no-show policy and seek approval for the evaluation of a no-show policy The DNP student and stakeholders discussed primary care no-show attributes to collect.

Do Phase. This phase consists of evaluating the practice adherence to a no-show policy. The DNP student met with office staff to discuss how the practice schedules and documents patient appointments in the EHR and SMS appointment notification system. The EHR was retrospectively audited to assess documentation of primary care no shows from March 2022 to February 2023.

Study Phase De-identified primary care no-show data from March 2022 to February 2023 was synthesized into Microsoft Excel and Power BI. Microsoft Power BI was used for data analysis and visualization. This was done by the DNP student to evaluate the financial impact of a no-show policy.

Act Phase Primary Care No-show data was presented to key stakeholders and recommendations were made for subsequent PDSA cycles.

Context

This quality improvement project was conducted at a private practice group with a primary care location in the northeast United States. The general population served at this practice are insured by Medicaid and Medicare, live below the poverty level, have multiple comorbidities such as hypertension, hyperlipidemia, type II diabetes mellitus and obesity. The primary care practice sees approximately 60-80 patients per day which amounts to approximately 300-400 patients on a weekly basis. The practice utilizes an EHR system named EPIC to schedule patient appointments.

Project Team Members and Roles

The practice CEO and practice manager's role is to review and approve the quality improvement project. The practice lead primary care Nurse Practitioner is the practice mentor onsite, who will help with the implementation and championing of the project. The DNP student will be the project leader with advisement from SHU DHCON faculty and evidence-based practice expert.

Key Stakeholders and Buy-In

Key stake holders included the CEO, Practice Manager, primary care nurse practitioners, nurses, medical assistants, and patients. Other stakeholders are the receptionists who schedule appointments and make follow-up visits.

Description of Practice Change

- Propose practice change with key stakeholders with the goal to evaluate a No-Show policy.
- Evaluate the current use of the SMS notification system and EHR to document missed appointments.
- Utilize data to deliver contextually relevant interventions that improve patient care and business operations.

Evaluation Plan

The DNP student will be onsite for two weeks to evaluate practice adherence to a no-show policy including process and documentation. The DNP student will review patient charts and all data collected will be organized into spreadsheets and analyzed. Data analysis will include no-show rate, SMS notification system, and financial impact.

Potential Barriers to Implementation

- Inaccurate documentation of no-shows in EHR
- Inaccurate documentation of patient attributes in EHR.
- Time-consuming to synthesize and analyze data into spreadsheets.

Timeline

- February 2023: Evidence Review and DNP project proposal presentation.
- March 2023: Ethical Merit Review and Data collection
- April 2023: Data collection, analysis, and evaluation
- April 14, 2023: Final DNP project Presentation
- April 21, 2023: Davis & Henley College of Nursing DNP Poster Presentation (see

Figure 1).

Resources

Resources include EHR access, Microsoft Excel and Power BI for data collection, analysis, and presentation.

Review for Ethical Considerations

This project does not require Sacred heart University Institutional Review Board approval because it is a quality improvement project (see Appendix F & G). The approval to implement the project has been received from the CEO and practice manager.

Project Implementation, Evaluation, ROI

Project Implementation

The quality improvement team discussed the no- show attributes to evaluate. Based on evidence, factors chosen were age, gender, visit type, time of appointment, confirmation status, zip code, and patient health status (Kheirkhah, et. al, 2016). The EHR was assessed for no- show documentation by auditing all scheduled primary care visits from March 2022 to February 2023. Patients who missed their appointment without contacting the practice within 24 hours before the visit were labeled in the EHR as a no-show. Patients who confirmed their appointment were labeled in the EHR as confirmed.

All de-identified patient no-show data was extracted from the EHR to a Microsoft Excel spreadsheet. The de-identified patient no-show data was then imported to Microsoft Power BI, a business intelligence software, for data analysis and visualization. The primary care no show data was presented to key stakeholders and recommendations were made for subsequent PDSA cycles.

Barriers to Implementation

The review of EHR data became a more detailed and lengthy process. Approximately, (8,584) scheduled appointments were carefully reviewed. The EHR Information Technology (IT) support department was contacted for assistance and provided access to creating patient reports with additional patient attributes. The EHR report provides patient diagnosis duplications and diagnosis reporting inconsistencies. To ensure accuracy of data, patient diagnoses were manually extracted for all scheduled primary care no-shows. Although every patient received a text message, we were unable to account for patients who opted out of receiving SMS appointment reminders.

Evaluation

Data retrieval included all primary care scheduled visits from March 2022 to February 2023, of all adult patients (18 years and older). Patient data was synthesized into Microsoft Excel spreadsheets and analyzed with Microsoft Power BI. Total time spent with data retrieval and analysis equated to approximately 65 hours.

Process Measures

To evaluate the adherence to the no-show policy, scheduling data was retroactively analyzed from March 2022 to February 2023. Patients who missed their appointment without contacting the practice 24 hours before the visit were labeled a No-Show in the EHR by office receptionists.

In November 2022, the practice implemented a short message service (SMS) appointment reminder system. The SMS notification system utilized is a HIPPA compliant chat robot application that conducts an on-line conversation via text using a Natural Language Processing (NLP) engine.

At the beginning and the end of every day the office receptionists generate patient schedules from the EHR. The de-identified patient list is exported to the SMS system. The SMS system sends appointment reminders to all patients, 72 hours prior to their appointment. The SMS system generates a list of unconfirmed patients 48 hours prior to the patient appointment. Unconfirmed patients were called by office receptionists and if confirmed by phone, the receptionist documented “confirmed” in the EHR. On the day of the appointment, a SMS appointment reminder and primary care practice address was sent to all patients.

Outcome Measures

During a 12-month period, there were (8,584) scheduled appointments in the primary care practice during the quality improvement period (see Figure 2). After review of (8,584) scheduled patients, there were (1,435) (17%) no-show occurrences, in comparison to the national average no show rate of 18% (Kheirkhah et. al, 2016) (see Figure 2). Of these (1,435) no-show patients, (59%) were women and (41%) were men (see Figure 3). The largest population of no-show appointments (23%) were between the ages of 51- 61 (see Figure 4). Most of the no-show appointments by visit type were follow up appointments; (69%) (see Figure 5). When analyzed by zip code, (74%) of no-show patients live within 20 square mile radius of the primary care practice (see Figure 6).

Data from the SMS system did not appropriately analyze SMS confirmations that were consistent with scheduled and documented confirmed appointments within the EHR (see Figure

7). During an 8-month period, no show appointments 4 months prior to SMS implementation (554) and 4 months post SMS implementation (344) were analyzed. There was a (38%) (53) decrease in the average monthly rate of no shows in the 4 months post SMS implementation (see Figure 8). No show appointments for patients between the ages of 51- 61 prior and post SMS implementation by gender and age were analyzed. There was a (23%) decrease in the number of women who missed their appointments post SMS implementation. There was a (52%) decrease in the number of men who missed their appointments post SMS implementation (see Figure 9). No-shows follow up appointments prior to SMS implementation was (397) and post SMS implementation was (209); a (47%) decrease post SMS implementation (see Figure 10). No-show appointments of patients with 0-10 chronic illness prior to SMS implementation was (427) and post SMS implementation was (258); a (40%) decrease post SMS implementation (see Figure 11). No show appointments of patients with Hypertension prior to SMS implementation were (254) and post SMS implementation was (152); a (40%) decrease in no-show patients with hypertension post SMS implementation (see Figure 12). No show appointments of patients with Hyperlipidemia prior to SMS implementation were (102) and post SMS implementation was (48); a (53%) decrease in no-show patients with Hyperlipidemia post SMS implementation (see Figure 13). No show appointments of patients with Type II Diabetes prior to SMS implementation were (152) and post SMS implementation was (98); a (36%) decrease in no-show patients with Type II Diabetes post SMS implementation (see Figure 14).

Return on Investment

When assessing the value of a medical intervention, a cost-effectiveness analysis is the most widely accepted method used by organizations to make informed decisions on whether to implement complex health interventions to reduce quality gaps (Wagner et al., 2020).

The SMS appointment reminder system cost the primary care practice ($30) to implement. The average cost of $218 was determined from the United States national average cost for a primary care visit (Kheirkhah, et. al, 2016). Prior to SMS implementation the potential revenue lost was ($30,302); this was calculated by the average number of no shows pre-SMS implementation (139) multiplied by the average cost of a primary care visit ($218). After SMS implementation the potential revenue lost was ($18,748); this was calculated by the average number of no shows post-SMS implementation (86) multiplied by the average cost of a primary care visit ($218). The return on investment (ROI) for SMS notification implementation was ($11,554) a (38%) increase in revenue. ROI was calculated by the average no show reduction (53) multiplied by the average revenue from a primary care visit ($218) (see Table15).

Key Lessons Learned

One of the key lessons learned was the value of good data quality and management. Raw EHR data is inherently disorganized and can be challenging with even the simplest of queries (Milinovich & Kattan, 2018). During the implementation phase, manual data extraction was time consuming and a pragmatic process. To ensure the cleanest and most robust data for future statistical analysis, data will need to be simplified and structured into Unified Medical Language System (UMLS) identifiers to save time (Milinovich & Kattan, 2018).

Sustainability Plan

The primary care practice adhered to the no-show policy and with the utilization of AI, decreased the number of no-show patients with chronic illnesses, follow up appointments and increased revenue. The PDSA method can be used for future improvement initiatives to decrease no-shows. The SMS notification system utilized by the practice, is powered by NLP understanding and can be used as a tool for patient surveys and building medical conversational interfaces for patient engagement and chronic care management.

This quality improvement project differs from historic evaluations because all patient no-show data related to patient demographics, appointment history and visit characteristics were pooled into an AI visualization tool, for rapid analysis and continuous improvement. Power BI is a simple to use business intelligence tool. Its interoperability makes it easy to aggregate data from otherwise disconnected databases into one data dashboard. The data can be refreshed within a few minutes once the data source is updated. Power BI can be used to provide individualized care for at risk patients using advanced analytics and holistic visualization of patient demographics and health status. Power BI can help mitigate unexpected challenges through real time analysis of patient data, clinical logistics, costs, and resource allocation.

This project demonstrates that providers can use scheduling data from the EHR to improve patient care through efficient scheduling practices. Power BI can continue to be used to integrate and analyze data from the EHR. Epic EHR, developed a proprietary algorithm for predicting no-shows and can be utilized to assess SMS frequency to reduce no shows (Coley et. al, 2022).

Dissemination

Implications of Project Results to Organization and Practice Community

Implications from the study suggest that AI can be utilized to uncover data driven insights that optimize clinical decision making and improve patient outcomes. Understanding the value of evaluating the cost of technology can provide senior leadership with insights that can inform decisions in lean economic environments.

Sharing Project Results

An executive summary and data dashboard was shared with the practice setting (see Appendix G for executive summary). A PowerPoint presentation was completed for the practice leadership and SHU community. As part of the DNP program course, the project was presented in poster format for the Davis & Henley College of Nursing faculty and students (see Appendix I).

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Appendix A

No-Show, Cancellation, and Rescheduling Policy

Thanks for trusting us with your medical care needs. When an appointment is scheduled, we try to allocate enough time to provide each patient with quality care. Therefore, if a patient needs to cancel or reschedule an appointment, be sure to get in touch with our office as soon as possible, no later than 24 hours before your scheduled appointment.

Please see our Appointment Cancellation/No Show Policy below:

- “No Show” shall mean any patient who fails to arrive for a scheduled appointment. “Same Day Cancellation” shall mean any patient who cancels an appointment less than 24 hours before their scheduled appointment.

- “Late Arrival” shall mean any patient who arrives at the clinic 15 minutes after the expected arrival time for the scheduled appointment.

- Effective July 1, 2021, any patient who fails to show or cancels an appointment and has not contacted our office with at least 24 hours’ notice will be considered a No Show and charged a $25.00 fee.

- Any established patient who fails to show or cancels/reschedules an appointment without 24 hours’ notice a second time will be charged another $25 fee.

- If a third, No Show or cancellation should occur, the patient may be dismissed from Advanced Cardiovascular Specialists.

- A 15-minute callback policy will be implemented to help facilitate missed appointments and same-day rescheduling when possible.

- The fee shall be charged to the patient, not the insurance company.

- As a courtesy, we will make reminder calls for missed and late appointments when time allows. If you do not receive a reminder call or message, the above Policy will remain in effect.

We understand that when an unforeseen emergency event occurs, that is out of your control and you may not be able to keep your scheduled appointment. If an emergency occurs, please get in touch with the office immediately to waive the no-show fee. You may contact the practice 24 hours a day, seven days a week at the numbers below. Should it be after regular business hours Monday through Friday or a weekend, you may leave a message. We will return your call as soon as possible.

Appendix B

Evidence Summary Table

Citation	Conceptual Framework	Design/ Method	Sample/Setting	Major Variables Studied and Their Definitions	Outcome Measurement	Data Analysis	Findings	Level of Evidence/Quality	Quality of Evidence: Critical Worth to Practice
Author Year Title County Funding	Theoretical basis for study		Number Characteristics Exclusion criteria Attrition	Independent variables IV1 = IV2 = Dependent variables	What scales used - reliability info (alphas)	What stats used	Statistical findings or qualitative findings	Level =	Strengths Limitations Risk or harm if implemented Feasibility of use in your practice
Article 1									

Oikonomidi et al., 2022. Predictive model-based interventions to reduce outpatient no-shows: a rapid systematic review	N/A	Systematic review of randomized controlled trials (RCTs) and non-RCTs	**Sample**: 8 Studies **Inclusion criteria:** (1) Randomized controlled trials (RCTs), nonrandomized controlled trials, and interrupted time series (2) Interventions based on predictive models and aiming to reduce no-shows or increase attendance, with any comparator (3) Conducted in outpatient care, with adults with any condition.	**IV1**= Predictive Modelling **IV2**= Usual scheduling practice **Dependent variables** = - Outpatient No shows - Costs - Acceptability - Equity	- Cochrane Risk of Bias tool (ROB 2)/ Risk Of Bias In Nonrandomized Studies of Interventions (ROBINS-I) - GRADE assessment	Risk Ratio (RR)	**Prediction model plus phone call reminders versus usual scheduling practice:** Median no-show RR was 0.61 (IQR 0.49, 0.68, min 0.49, max 0.75). **Costs, acceptability, and equity:** - One RCTs reported an effect of predictive model-based phone call reminders on the mean relative value units per patient, absolute difference 0.13, 95% CI 0.02 to 0.28. - In another RCT, the authors conducted post intervention debriefing with 8 physicians and managers and found that they considered the intervention successful, but that there were issues with	Level I/High quality	**Strengths**: - Appraisal of the evidence using the ROB 2, ROBINS-I, and GRADE tools. - Identified effective predictive model-based interventions and mapped important evidence gaps. - The findings can be used to guide future research and support the current implementation of predictive models in real-life care settings. **Limitations** - A meta-analysis could not be

			(4) Reporting at least 1 outcome domain indicating appointment attendance (ie, no-shows, cancelations, attended appointments **Exclusion criteria:** (1) Studies lacking a contemporaneous control group (eg, studies using historical or simulated controls), interrupted time series with fewer than 3 data collection points before and 3 after the intervention. (2) Studies in pediatric				the workload resulting from achieving fewer no-shows and the workload associated with implementing the intervention. - No information was reported on equity **Prediction model plus text message reminders versus usual scheduling practice:** - Median no- show RR 0.91, interquartile range 0.90, 0.92, min 0.89, max 0.93 **Costs, acceptability, and equity:** - A sensitivity analysis found no evidence of heterogeneous intervention effect on no-show rates by age, sex,		performed due to the incomplete and unclear reporting of outcome data, and heterogeneity in outcome measures and interventions. - Although the range of observed RR is presented, this does not account for differences in the relative sizes of the studies. - A rapid review, screening was completed by 1 researcher. Although the agreement between reviewers was excellent in the independent

			settings (ie, participants were under 18 years old according to the inclusion criteria) or in general practitioner offices, and studies focused exclusively on vaccination appointments or population screening.				race, or amount of copay. - No information was reported on costs and acceptability **Prediction model plus patient navigator versus usual scheduling practice:** - No-shows RR 0.55, 95% CI 0.46–0.67 and cancelations RR 1.16, 95% CI, 1.04–1.29 **Costs, acceptability, and equity:** - The average net income associated with this intervention was $5000 per month. - In a subgroup analysis (unreported numeric data, odds ratios of appointment attendance for race, language, gender, age, and insurance subgroups presented		screening of 10% of retrieved titles, it is possible that we missed some eligible studies - The review included findings from 8 studies. - Findings may not generalize to certain contexts, such as low-income countries and pediatrics.

							in figures), the effect of the patient navigator intervention was significant for anglophone patients but not for other language groups, for white and African American patients but not Hispanic and Asian patients, and for Medicare and commercial insurance holders but not for Medicaid holders and self-paying patients. - Regarding age, the intervention effect was significant only for patients in the 40–69 age group. - No information was reported on acceptability **Prediction model plus overbooking versus usual scheduling practice:** - In 2 RCTs and 1 non-RCT (analyzing		

							31,766 appointments), information on the risk of no-show was used to make overbooking decisions. - Outcome data could not be summarized, because the 3 studies used different outcomes. Due to the risk of bias, inconsistency, indirectness, and imprecision in the available evidence, there is very low certainty whether there is an effect of predictive model based overbooking on appointment attendance. **Costs, acceptability, and equity:** - **Cost**: Predictive model-based overbooking was associated with a		

							relative increase of 15.4% in hourly revenue in the MRI clinic (absolute difference of 8.14$, unreported 95% CIs and significance), but with higher daily overtime costs in endoscopy (absolute difference of 26.13$). **Acceptability**: 1 RCT reported that on intervention days, clinics ran longer by an average 34 min compared to control days (absolute difference 0.47 h [95% CI, 0.06–0.88, P..02]). One non-RCT reported a nonsignificant increase of 6.2 min in patient in-clinic wait time (relative difference 3.66%) and 10 min in staff overtime (4.05%, unreported 95% CIs and significance).		

							- In 1 RCT, African Americans were twice as likely as whites to take up “fast track” appointments made available by overbooking (adjusted odds ratio 1.99, 95% CI, 1.26–3.17).		
Article 2									
Salazar et. al, 2022.No-Show in Medical Appointments with Machine Learning Techniques: A Systematic Literature Review	N/A	Systematic review	Sample :24 studies **Inclusion Criteria :** **-** Contain an abstract; Be written in English. Have been published between 1 January 2017 and 1 January 2022 **Exclusion criteria:**	**IV:** Machine Learning **Dependent variables** = No shows	- Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)	AreaundertheROCCur	**How much data is used to train machine learning models for no-show prediction?** - In total, 18 different data sets were used in the 24 studies found. Two studies did not report the volume of data used. Only five studies used an amount of data greater than one million records, while the others used around 120 thousand records, on average.	Level I/ High quality	**Strengths** **-** The accuracy of the models developed with a smaller amount of data was higher or equivalent to the others. - The results indicate that even with more complex algorithms available in artificial intelligence, decision trees algorithms are still the best choice to handle the no-show in medical appointments

			- Medical attendance prediction in other fields than health appointments. Medical attendance prediction without the use of machine learning techniques. Literature reviews			v e	On average, 17 attributes were used to build the model in each work. - With regard to the no-show rate present in the initial dataset, the highest rate observed was 85%. - The average absenteeism rate remained around 18% and the lowest rate was 10% **Which machine learning algorithms are used in the predictive models and which of these presented the best performance?** - The algorithms with the best performance in the works found were Gradient Boosting, Decision Trees, and Random Forest. - Random forest was selected as the most		**-** The data quality is evidenced as an important factor in terms of building the machine learning models. Most have derived new attributes from existing ones from the original dataset or added new datasets to improve the model's comprehensiveness. - Re-balancing techniques were performed in most of the datasets in order to not bias the model training. - The studies presented research and useful contributions to data privacy management in different concepts and scenarios. **Limitations**: **-** The results revealed that the solutions used to mitigate medical appointments no-show

							suitable for building the models **What characteristics most influence patients not to attend a scheduled medical appointment?** - The most influential factors in the built model are related to the patient's age, whether the patient missed a previous appointment (previous no-show), and the distance between the appointment and the patient's scheduling (lead time). Other attributes, such as the geographical distance from the patient's home to the clinic location, appointment date and shift, medical specialty, and whether there was prior confirmation of the appointment, had			with machine learning techniques do not present practical results of reducing abstentions based on the solutions presented. Except for one, which showed in their experiments that there was a 3.4% reduction in no-shows after the deployed solution.

							a low impact on the algorithms. **What is the no-show rate reduction in medical appointments that solutions developed with the help of machine learning techniques achieve?** - One study reported a reduction from 19.3% to 15.9% in abstentions, by sending a reminder to 25% of the patients who were pointed out by the model as at greater risk of not attending the appointment - Other studies did not present metrics that demonstrate the reduction of no-shows in medical appointments, after the machine learning model development. - In order to avoid		

							the high cost of sending reminder notifications to every patient, some studies have proposed to optimize the sending and make them only for patients who are at high risk of no-show.		
Article 3									
Coley et. al, (2022). Pragmatic Randomized Study of Targeted Text Message Reminders to Reduce Missed Clinic Visits.	N/A	RCT	**Sample**: 125,076 primary care visits and 33,593 mental health visits **Inclusion:** - visits scheduled 4 business days or more in advance and were classified as “high-risk” for no-show, defined as an Epic no-show risk in the top	**IV1**: receive a text message 3 business days before the visit, in addition to the usual text message reminder 2 business days before the visit. **IV2**: receive a text	Logistical regression	Relative Risk	- A total of 125,076 primary care visits (41.3%) had a predicted no-show risk at or above 5.1% (40th percentile cut-off) and were randomly assigned 1 text message (n = 62,519) or 2 reminder text messages (n = 62,557). A total of 33,593 mental health visits (38.4%) had a predicted no-show risk at or above 21.1% and were assigned for randomization during the study period.	Level II/ High quality	**Strengths:** - An additional text message in advance of visits at high chance of being missed was effective in reducing no-shows in primary care and mental health visits, and in reducing same-day cancellations of primary care visits. - Utilizing a risk prediction model to target reminders may promote efficient use of health care resources - By sending an additional text message reminder to high-risk

			40% of risk predictions **Exclusion:** - Patients who have opted- out of receiving text messages	message 2 business days before the appointmen t. **Dependent variables** = - No show rate - Same day cancelation s			- 16,830 mental health visits were sent only one text message reminder and 16,763 were sent an additional text message. The percentage of visits of each type included in the study deviated slightly from 40% due to variation in the distribution of risk predictions between visits in the retrospective sample used to select cut-offs and those during the study period. - Results indicate that the intervention reduced the chance of no-shows in both primary care and mental health visits and reduced the chance of same-day cancellation in primary care visits. The estimated relative risk (RR) of no-show		visits we achieved higher efficiency at lower costs to the health system (compared to sending a message to all visits) and limited unnecessary notifications to patients with a high likelihood of attending their scheduled visit **Limitations:** **-** Monitor for a change in patient requests to opt out of text messages among patients with visits in the intervention arm. - This approach involves additional costs of implementing a risk prediction model within the system. Risk-based targeting of additional text message reminders can be further improved by developing a risk model tailored to a

							between the control and the intervention arm in primary care visits was 0.93 (95% confidence interval, CI, between 0.89 and 0.96). The no-show risk for that visit will decrease by 7% if an additional text message is sent for any given primary care visit with a high estimated no-show risk. Sending an additional text message reminder also reduced same-day		particular population. A more precise risk model could improve the effectiveness of the intervention and may also be used to inform more resource intensive interventions (eg, live reminder phone calls by patient access representatives).
Article 4									
Robotham et.al, 2016. Using digital notifications to improve attendance in clinic: systematic	N/A	Systematic Review and Meta -analysis	**Sample**: 26 studies **Inclusion**: - Studies examining the effect of electronic text notifications on the attendance of prescheduled	**IV1:** Text-based electronic notifications **Dependent Variables**: - Rate of attendance	- Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) - Clopper Pearson	Risk Ratio	- Patients who received notifications were 23% more likely to attend clinic than those who received no notification (risk ratio=1.23, 67% vs 54%). Those receiving notifications were	Level I/ High quality	**Strengths:** - Electronic text notifications improve attendance and reduce no shows across healthcare settings. - Sending multiple notifications could improve attendance further

review and meta-analysis			healthcare appointments. - Studies were only included in the primary analysis if they included a control group which received 'no notifications. In cases where studies had multiple comparison groups (eg, electronic text notifications vs voice notifications vs no notifications), the data from alternative intervention groups were included in a secondary analysis **Exclusion:** - Data relating to patients	- Rate of non-attendance - Rate of rescheduled appointments - Rate of cancelled appointments	confidence interval		25% less likely to 'no show' for appointments (risk ratio=.75, 15% vs 21%). - Results were similar when accounting for risk of bias, region and publication year. - Multiple notifications were significantly more effective at improving attendance than single notifications. Voice notifications appeared more effective than text notifications at improving attendance.		**Limitations** - Multiple reminders did not make a significant difference in reducing 'no shows

			attending non-scheduled drop-in clinics or where patients were reminded to book future appointments, or health outcomes other than clinic attendance. - Studies not published in the peer-reviewed literature or presented at academic conferences or which lacked sufficient information to be included in the meta-analysis after contacting study authors (ie, studies failing to report the number of patients allocated to receive an electronic text						

			notifications intervention).						
Article 5									
Lance et. al, 2021.Comparison Between Short Text Messages and Phone Calls to Reduce No-Show Rates in Outpatient Medical Appointments	N/A	Randomized controlled trial	**Sample**: 306 patients **Setting**: Primary Care Clinic **Inclusion criteria:** - All patients older than 18 years who were waiting for an internal medicine appointment between July 2, 2018, and September 20, 2018. **Exclusion criteria:** - Users who	**IV1:** Telephone Call **IV2:** Short test messages (SMS) **Dependent variable:** - No Shows	Chi-square	P < .05 = statistically significa	- The lowest percentage of no-show (9.5%) occurred in the telephone call group - The SMS group presented at 21% and the no-intervention group at 22.8% (P = .025). **Cost-effectiveness analysis** - The study concluded that although SMS are cheaper than telephone calls, the latter was much more cost-effective. - For each dollar invested in SMS, there is a return of $2.67 while the return	Level II/High Quality	**Strengths:** - Telephone calls proved to be a superior strategy to text messaging - Patients with the last visit within a greater time frame would benefit more by the reminder. **Limitations** - Low external validity. Studies published with a similar methodology to this survey, comparing telephone calls, SMS, and a control group, obtained heterogeneous results

			did not have a cell phone and those who at the time of recruitment had no identification document were excluded			n t	on investment related to telephone calls is $15.24. - The investment of $141,000 in telephone calls could avoid a loss of around $2.1 million per year.		
Article 6									
Kheirkhah et.al, 2016. Prevalence, predictors and economic consequences of no-shows.	N/A	Retrospective Cohort Study	**Sample**: > 76,000 patients in 10 clinics **Setting**: VA Medical center **Inclusion criteria:** - No-show data for 12 years (fiscal year 1997–2008) **Exclusion criteria:**	**IV**: Completed Appointment **IV2**: Missed appointment **Dependent variable:** **-** No Show Rates - Cost - Gender - Age - Hospital size - Appointme	Kolmogorov-Mirnov test	Two-way ANOVA	- The mean no-show rate was 18.8 % (2.4 %) in 10 main clinics with highest occurring in subspecialist clinics. No-show rate in the women clinic was higher and the no-show rate in geriatric clinic was lower compared to general primary care clinic (PCP). - The no-show rate remained at a high level despite its reduction by a centralized phone reminder (from 16.3 % down to 15.8 %).	Level: IV/Good quality	**Strengths**: - Provides a large sample size and longitudinal data to evaluate the prevalence and economic consequences over a long period of time. - The huge cost of no shows combining with other undesirable consequences of no-show motivated management to use any method to decrease the overall cost of health care tremendously. **Limitations:**

				nt time on no-show - Reminder-letter system - Centralized phone system			- The results showed that the current implemented reminder system had modest effect on no show		- Many factors affect no-show, including age, gender, type of clinic, time of appointment (day and month), distance, employment status, and patient health status. Any promising methodology to predict and reduce no-show should consider and examine the effect of these factors on prediction model.
Article 7									
Marbouh et.al, 2020. Evaluating the Impact of Patient No-Shows on Service Quality	N/A	Case Control Study	**Sample**: Retrospective data on patient no shows **Setting**: Radiology department at a leading hospital in Dubai **Inclusion:**	**IV**: No Shows **Dependent variable:** **-** Patient related issues - Environmental Issues	Marginal regression model	Interrelationship of no shows and some variables are examined.	No-shows are high due to multiple factors, such as patient behavior, patients' financial situation, environmental factors and scheduling policy	Level: IV/Good quality	**Strengths**: - By using the Electronic Health Records (EHRs), healthcare providers can access patients' no-show history and build predictive models that can assess each patient and their probability of no-show. By considering the no-

			Informal discussions were conducted with the hospital staff, including managers, physicians, nurses and scheduling assistants to validate if patient no-shows that have been identified	- Financial Issues - Scheduling Relates Issues					show record of patients and their probability of missing their appointment, predictive analytics tools and methods can be used to create overbooking conditions. These models can avoid the hospital the potential costs of no-shows. **Limitations:** - Sample size not provided - Factors affecting no-shows for this particular hospital were unique including fear and anxiety.
Article 8									
Boone et. al, 2022. How scheduling systems with	N/A	Controlled Trial without Randomization	**Sample**: **Setting-** **Inclusion criteria:**	**IV**: **IV2** **Dependent variable:**	Difference in Difference		The program did not change the number of visits by chronic patients eligible to receive the reminder but visits from other	Level: III/Good quality	**Strengths**: **Limitations:**

automated appointment reminders improve health clinic efficiency			**Exclusion criteria:**	**-** No Show Rates			patients ineligible to receive reminders increased by 5.0% in the first year and 7.4% in the second - Clinics treating more chronic patients and those with a relatively younger patient population benefited more from the program - Automatic appointment reminders were effective in increasing clinic ability to care for more patients, likely due to timely cancelations.			

Appendix C

Levels of Evidence Synthesis Table

PICO Question: In outpatient care (P) does the adherence to a no show/cancellation policy (I) compared to non-adherence (C) impact revenue (O) over a 12-month period (T)?

Level of evidence	1	2	3	4	5	6	7	8
Level I: Systematic review or meta- analysis	**X**	**X**		**X**				
Level II: Randomized control trial			**X**		**X**			
Level III: Controlled trial without randomization								**X**
Level IV: Case-control or cohort study						**X**	**X**	
Level V: Systematic review of qualitative or descriptive studies								
Level VI: Qualitative or descriptive study, CPG, Lit Review, QI or EBP project								
Level VII: Expert opinion								

LEGEND **1=** Oikonomidi et al., 2022. **2=** Salazar et. al, 2022. **3=** Coley, R. Y., 2022 **4=** Robotham et.al, 2016. **5=** Lance et. al, 2021. **6=** Kheirkhah et.al, 2016. **7**= Marbouh et.al, 2020. **8=** Boone et. al, 2022.

Appendix D

Outcome Synthesis Table

PICO Question: In outpatient care (P) does the adherence to a no show/cancellation policy (I) compared to non-adherence (C) impact revenue (O) over a 12-month period (T)?

↑, ↓, —, NE, NR, ✓ (select symbol and copy as needed)	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
NSR	↓	↓	↓	↓	↑	↓	↑	↓
CE	✓	✓	✓	✓	✓	✓	✓	✓
AN	✓	✓	✓	✓	↑	✓	✓	✓

SYMBOL KEY

↑ = Increased, ↓ = Decreased, — = No Change, **NE** = Not Examined, **NR** = Not Reported (introduced at beginning but never reported at the end), ✓ = applicable or present

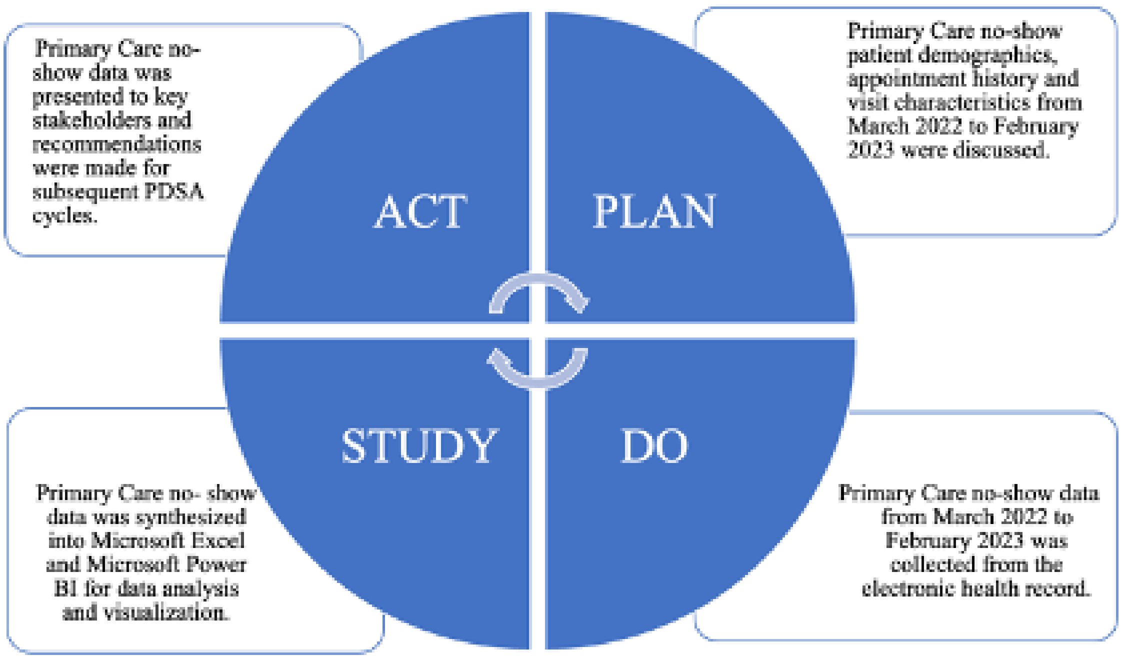
NSR= No Show Rate **AN**= Appointment Notification **CE**= Cost Effectiveness

LEGEND

1= Oikonomidi et al., 2022. **2=** Salazar et. al, 2022. **3=** Coley et. al., 2022. **4=** Robotham et.al, 2016. **5=** Lance et. al, 2021. **6=** Kheirkhah et.al, 2016. **7**= Marbouh et.al, 2020. **8=** Boone et. al, 2022.

Appendix E

PDSA Cycle



Appendix F

Ethical Review

Differentiating Quality Improvement and Research Activities Tool

Question	**Yes**	**No**
1. Is the project designed to bring about immediate improvement in patient care?	X	
2. Is the purpose of the project to bring new knowledge to daily practice?	X	
3. Is the project designed to sustain the improvement?	X	
4. Is the purpose to measure the effect of a process change on delivery of care?	X	
5. Are findings specific to this hospital?	X	
6. Are all patients who participate in the project expected to benefit?	X	
7. Is the intervention at least as safe as routine care?	X	
8. Will all participants receive at least usual care?	X	
9. Do you intend to gather just enough data to learn and complete the cycle?	X	
10. Do you intend to limit the time for data collection in order to accelerate the rate of improvement?	X	
11. Is the project intended to test a novel hypothesis or replicate one?		X
12. Does the project involve withholding any usual care?		X
13. Does the project involve testing interventions/practices that are not usual or standard of care?		X
14. Will any of the 18 identifiers according to the HIPAA Privacy Rule be included?		X

Appendix G

IRB Exemption Status

Subject: IRB#230327C - Exempt Status Request
Date: Wednesday, March 29, 2023 at 7:45:35 AM Pacific Daylight Time
From: Taber, Prof. Christopher B.
To: Harding, Adrianne S.
CC: Alp, Feride F. 'Funda', Londo, Madeline C.
Attachments: image001.png

Dear Applicant,
Thank you for your submission to the IRB requesting exempt review. Based on the application submitted, the IRB is pleased to approve your submission and we wish you great success in your research.

Sincerely,
Christopher Taber
Chair, IRB

Christopher B. Taber, PhD, CSCS*D, USAW3, EP-C, PES
Director, Exercise and Sport Science M.S. Program
Associate Professor
College of Health Professions
Sacred Heart University
(203) 396-6342

To learn more about the M.S. in Exercise and Sport Science program, click here.

To see where our M.S. alumni are working, click here.

Appendix H

Executive Summary

No- shows are a global problem that creates a significant challenge for the healthcare system. When a patient misses an appointment, it decreases health care staff productivity, creates a waste of resources and negatively impacts revenue (Lance et. al, 2021). Current evidence supports interventions that incorporate voluminous data and artificial intelligence with strategies such as overbooking, appointment notification systems and financial incentives to reduce outpatient no-shows (Oikonomidi et al., 2022). Medical scheduling systems and machine learning algorithms can work as an efficient tool to understand appointment attendance in primary care. Evaluating the impact of a no-show policy to improve primary care attendance provides insights into individual practice sites and can inform decisions.

For this project, the Plan-Do-Study-Act method was used to evaluate an outpatient primary care office adherence to a no-show policy and its impact on practice revenue based on current evidence. In the Plan phase, no-show and demographic attributes from March 2022 to February 2023 were discussed. In the Do phase, the no- show data was collected from the electronic health record (EHR). For the Study phase, no- show data was analyzed. In the Act phase, the no-show data was presented to the key stakeholders at the primary care practice and recommendations were made for subsequent PDSA cycles.

During a 12-month period, the primary care practice reported 1435 (17%) no-show occurrences, in comparison to the national average no show rate of 18%. The practice implemented a short message service (SMS) appointment notification system. There was a 38% decrease in the average monthly rate of no shows in the 4 months post SMS implementation. With the United States national average cost of $218 for a primary care visit, a return on investment for SMS implementation was $11,554. Implications from the study suggest that no show patients have greater than 10 chronic illness' and were missing follow up visits. SMS implementation was shown to decrease the number of no-show appointments of patients with chronic illnesses and missed follow up appointments. Limitations included retrospective data analysis and data management. Creating customizable EHR data can be used to train predictive models and identify factors that have a higher impact on missed appointment rates. In summary, appointment reminders reduce no-shows. Artificial intelligence can optimize solutions to mitigate no-shows. Predictive models and machine learning can be utilized to detect patterns in identifying appointments at high risk of no-show and guide practice decision making. Reducing no-show rates can decrease the cost on the healthcare system, improve resource efficiency and patient outcomes while decreasing loss of revenue.

Appendix I

DNP Project Poster Presentation

DR. SUSAN L. DAVIS, R.N., & RICHARD J. HENLEY COLLEGE OF NURSING
Sacred Heart University

Evaluating the impact of a No- Show Policy: A Quality Improvement Project

Adrianne S. Harding BSN RN DNP (student), Dr. Constance Glenn DNP, MSN, APRN, FNP-BC, CNE
Janice Tavares APRN, FNP-BC

SIGNIFICANCE/BACKGROUND

- No- shows are a global problem that creates a significant challenge for the healthcare system. When a patient misses an appointment, it decreases health care staff productivity, creates a waste of resources and negatively impacts revenue (Lance et. al, 2021).
- No-shows have a direct correlation with negative health outcomes and are an independent predictor for increased use of acute care and emergency department services. (Oikonomidi et al., 2022).
- Current evidence supports interventions that incorporate voluminous data and artificial intelligence with strategies such as overbooking, appointment notification systems and financial incentives to reduce primary care no-shows (Oikonomidi et al., 2022). Artificial intelligence can work as an efficient tool to understand appointment attendance and optimize solutions to mitigate no-shows in primary care.

PURPOSE

To evaluate Advanced Cardiovascular Specialist (ACS) adherence to a no-show policy, its impact on practice revenue and provide recommendations to improve primary care attendance.

PROJECT GOALS

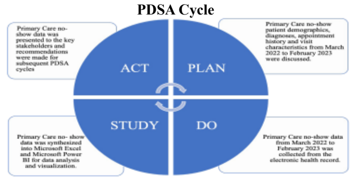
- Evaluate the adherence to a no-show policy
- Evaluate the current use of a short message service (SMS) notification system and the electronic health record (EHR) to schedule and document primary care appointments.
- Evaluate the financial impact of a no-show policy in primary care from March 2022 to February 2023.

METHOD

Design: EBP-QI project

Setting/Population: Advanced Cardiovascular Specialist/ Primary Care

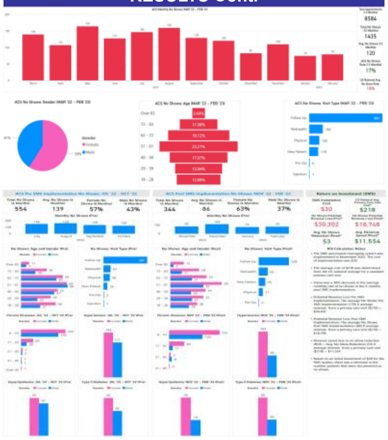
PDSA Cycle



RESULTS

SMS Notification System

RESULTS Cont.



Discussion

The implementation of a SMS appointment reminder system reduces no-shows in primary care. Artificial intelligence can optimize solutions to detect patterns in identifying appointments at high risk of no-show and guide practice decision making. Reducing no-show rates can decrease acute care and emergency department visits, decrease the cost on the healthcare system, improve resource efficiency, patient outcomes and decrease loss of revenue.

References or information contact: Hardinga2@mail.sacredheart.edu

Figure 1. Project Timeline

Figure 2. Monthly No-Shows

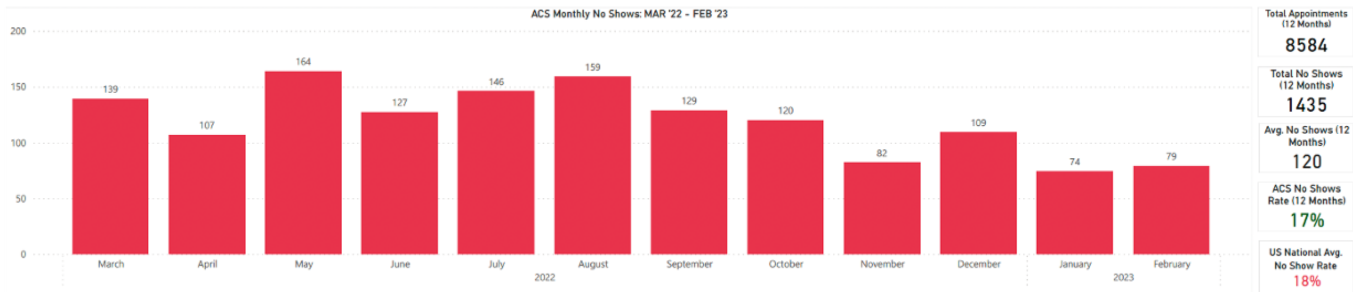


Figure 3. No-Shows by Gender

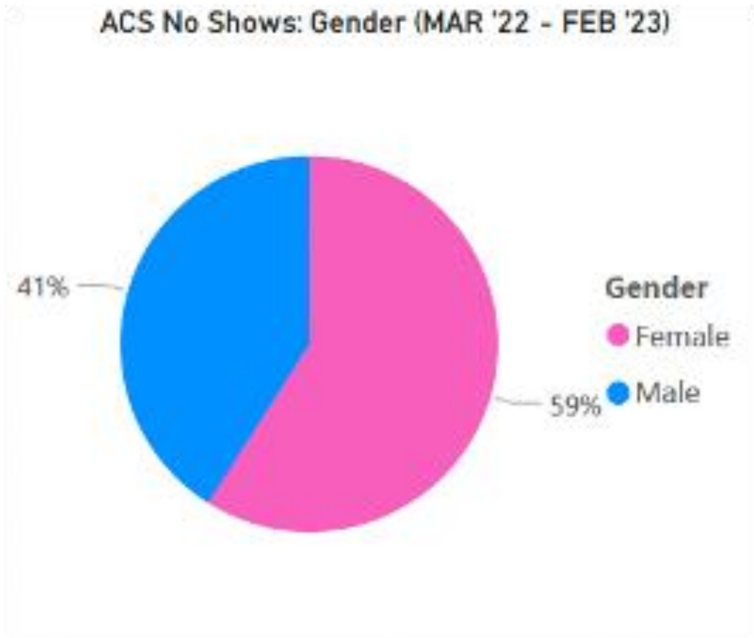


Figure 4. No- Shows by Age

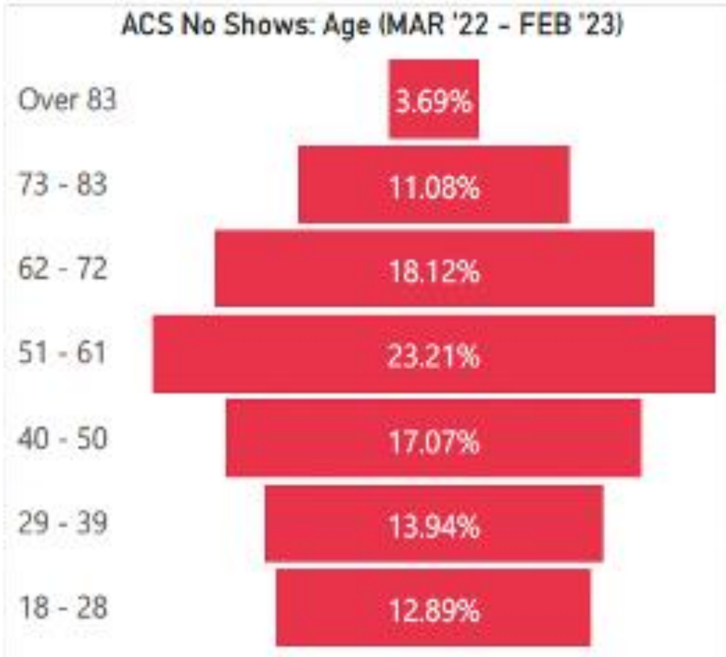


Figure 5. No- Shows by Visit Type

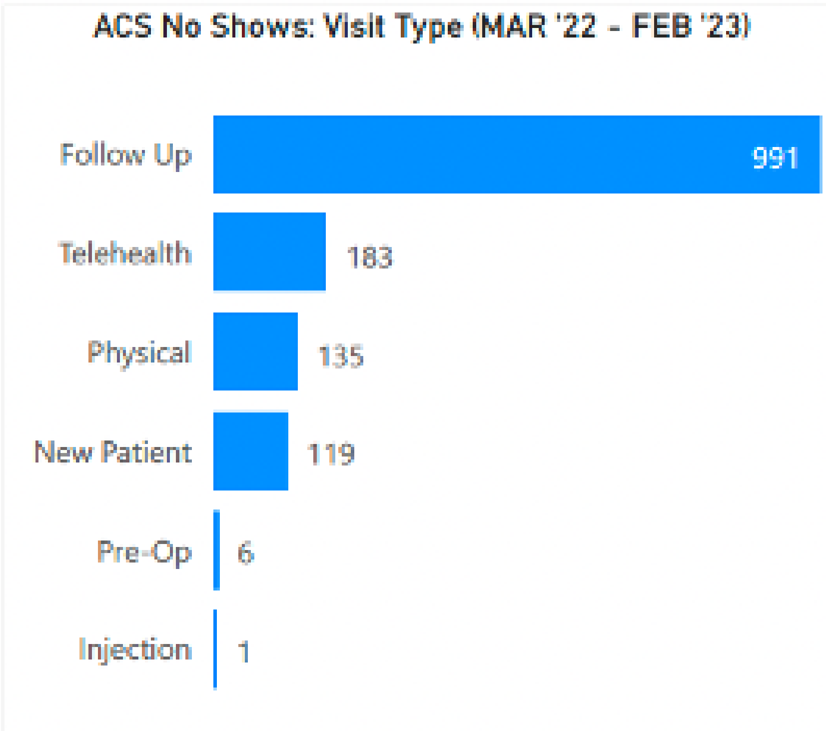


Figure 6. No-Show by Zip Code

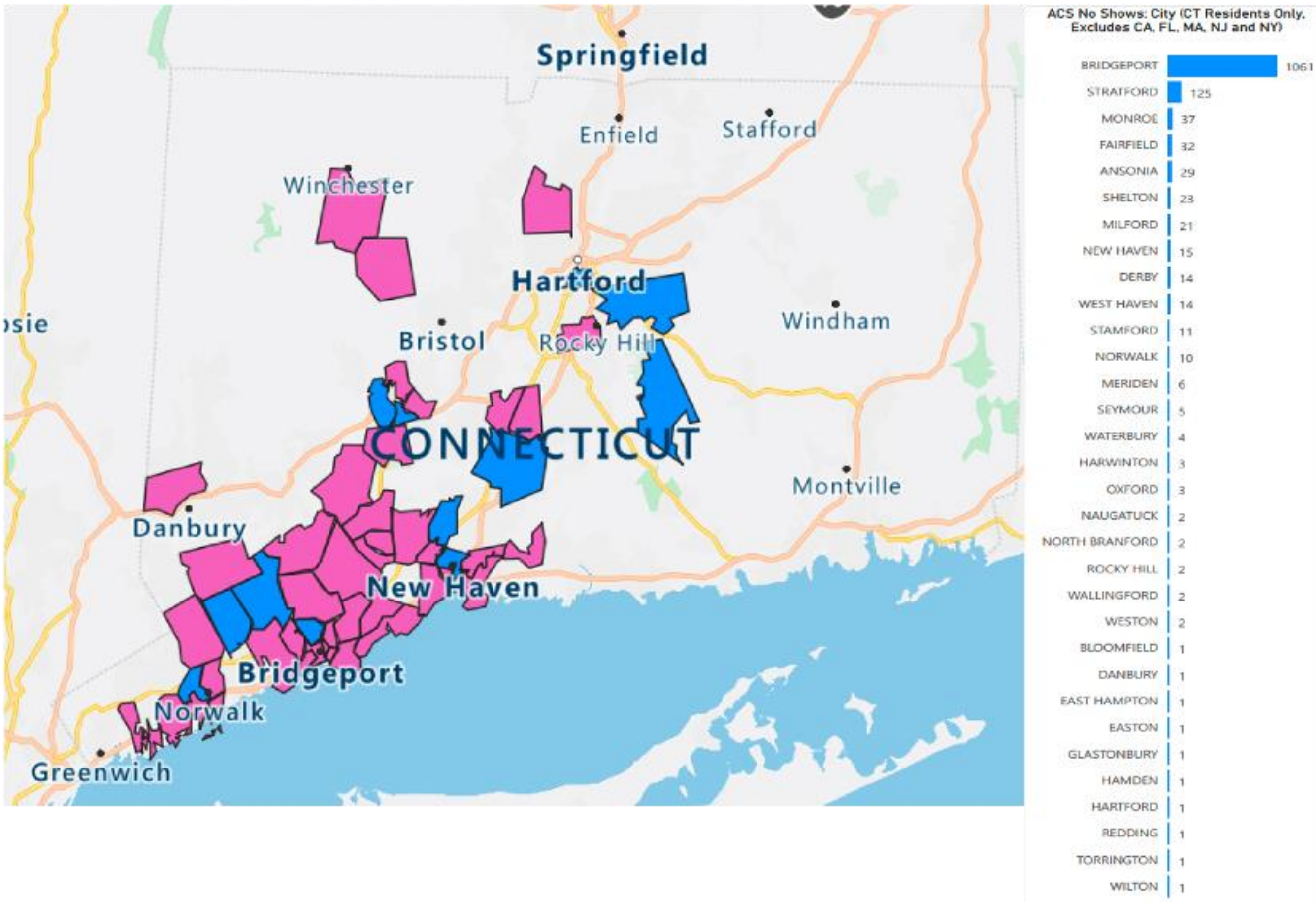


Figure 7. No- Show Confirmation Status

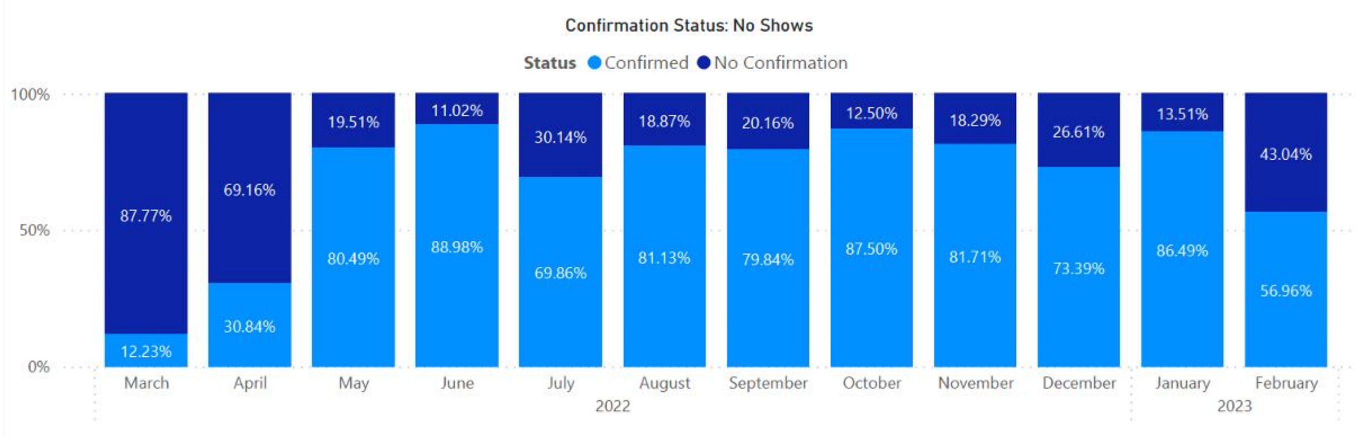


Figure 8. No- Shows Pre and Post SMS Implementation

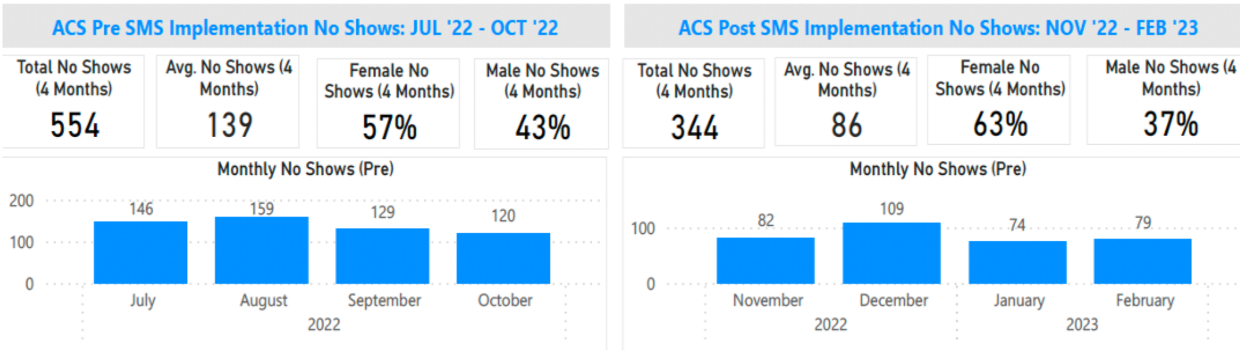
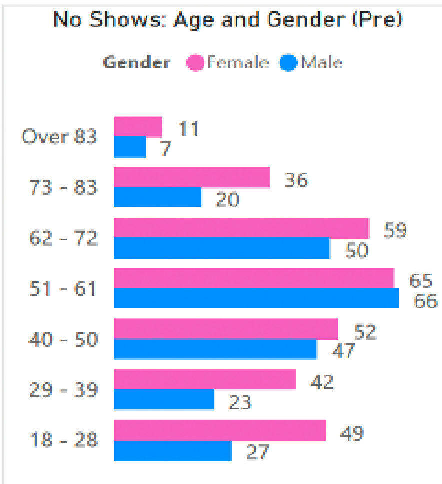


Figure 9. No- Shows Pre and Post SMS Implementation by Age and Gender



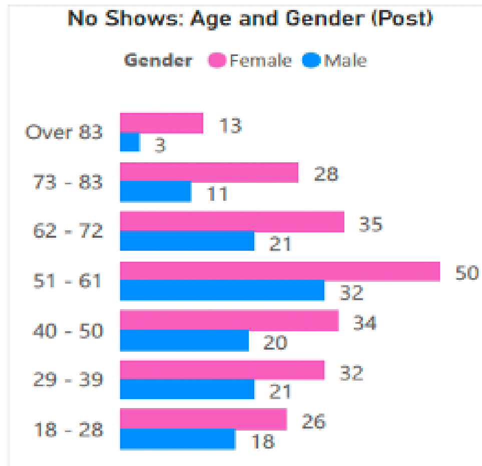
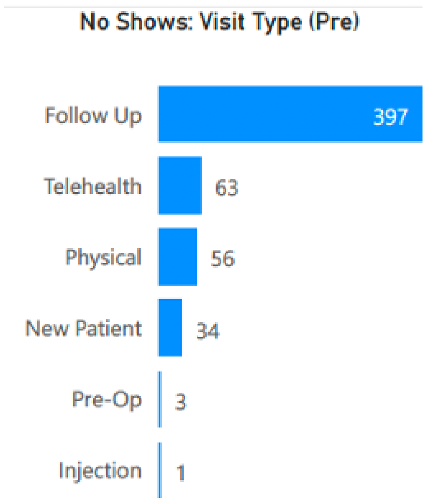


Figure 10. No- Shows Pre and Post SMS Implementation by Visit Type



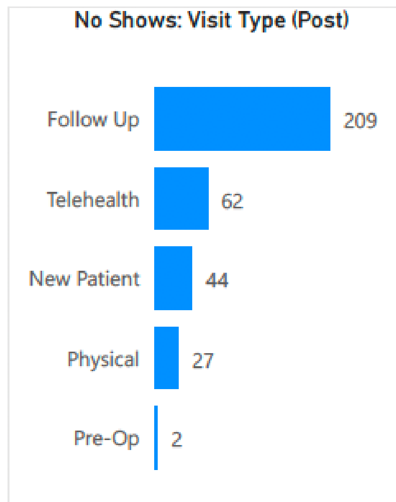
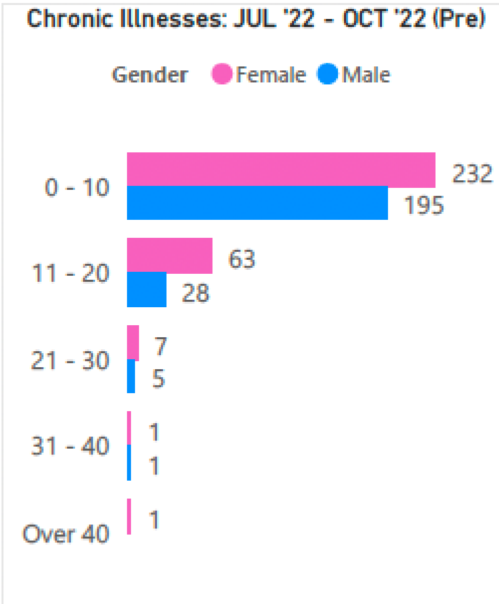


Figure 11. No- Shows Pre and Post SMS Implementation by Chronic Illness



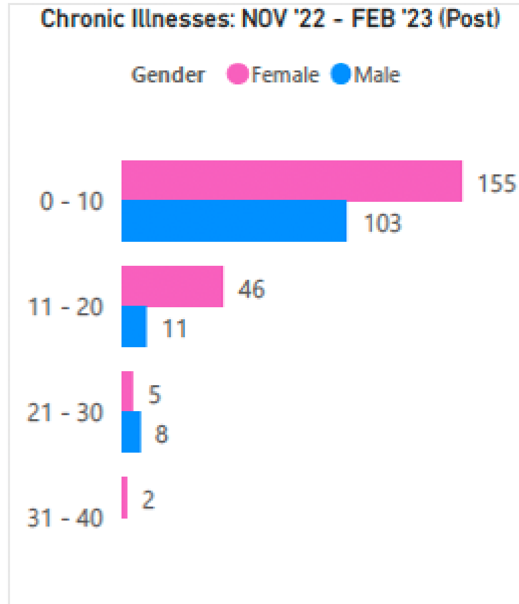
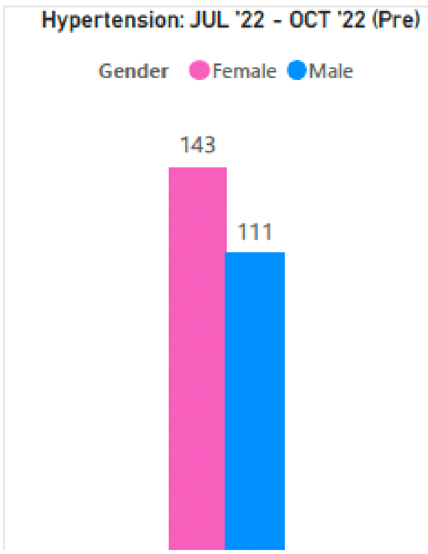


Figure 12. No- Shows Pre and Post SMS Implementation by Hypertension



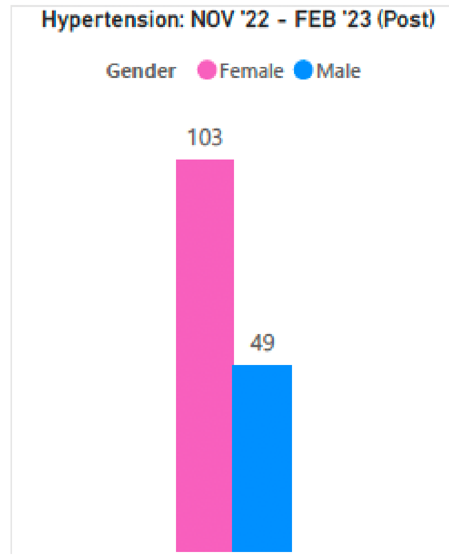
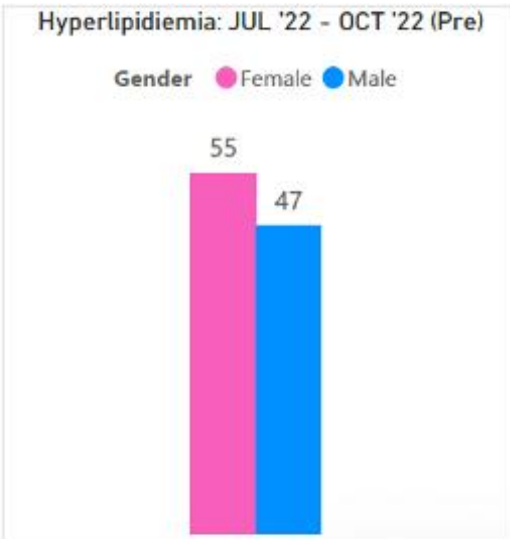


Figure 13. No- Shows Pre and Post SMS Implementation by Hyperlipidemia



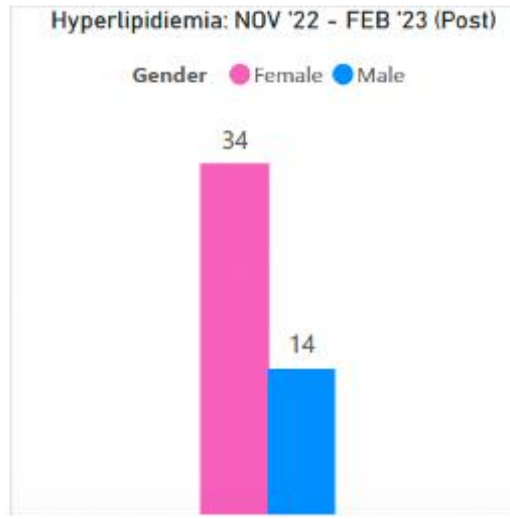
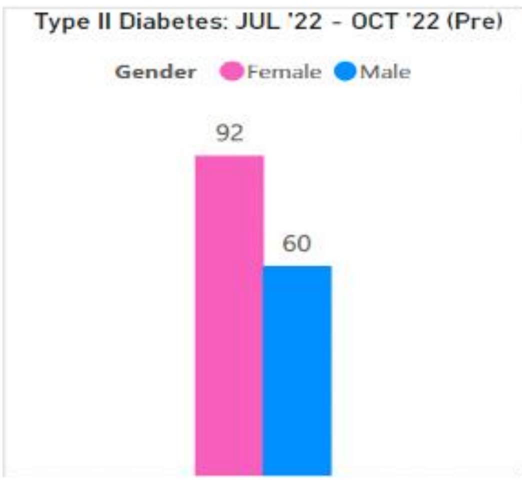


Figure 14. No- Shows Pre and Post SMS Implementation by Type II Diabetes



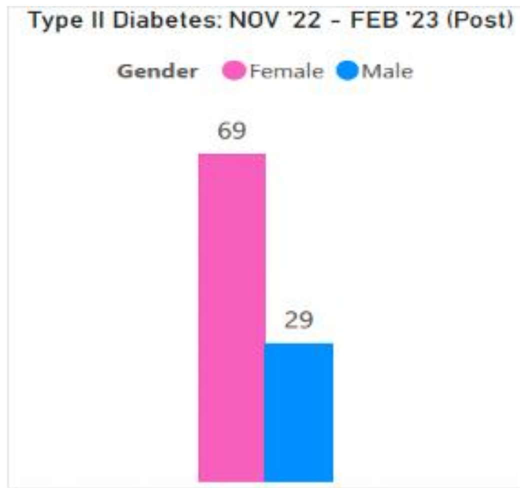


Figure 15. No- Shows Pre and Post SMS Implementation Return on Investment