Targeted Outreach to Reduce No-Show Rates: A Quality Improvement Project

Eaba Dechasa, PMHNP-DNP Candidate

Oregon Health & Science University, School of Nursing

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Submitted to: Kasey McCracken, MPH, DNP, PMHNP-BC

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Abstract

Background: No-shows are a common challenge that adversely affect both healthcare systems and patient outcomes. This issue is widespread and impacts healthcare institutions in various settings. Among these, is an outpatient mental health clinic which is currently experiencing a 20% no-show rate.

Aim: Project aimed to reduce no-shows at an outpatient psychiatric facility by identifying patients at an elevated risk of nonattendance using a predictive model based on a patient's no-show history and then conducting targeted outreach to those identified as high-risk.

Methods: A list of high-risk individuals was constructed weekly for the pilot nurse practitioner's panel. Those identified as high-risk would then receive a guided phone call from a nurse practitioner student as part of targeted outreach efforts. Pre- and post-implementation no-show rates were compared using retrospective and prospective data to evaluate the project's effectiveness and model performance.

Results: The project did not improve no-show rates compared to baseline values, with no-show rates increasing from 18.4% pre-intervention to 35.3% post-intervention, a statistically significant change at the $p<0.05$ level. The model's performance exhibited a modest ability to identify patients at an elevated risk of nonattendance, with sensitivity ranging from 42% - 46% and a specificity of 86% - 88%.

Conclusion: A predictive model based on a single variable (no-show history) may be insufficient to reliably identify patients at an elevated risk for missing appointments. In addition to poor predictive model performance, low successful patient contact (35%) likely limited the intervention's ability to influence attendance behavior.

Introduction

Problem Description

A no-show (NS) is defined as an instance where a patient fails to attend a prearranged visit without providing prior notice (Chapman et al., 2022; Toffaha et al., 2025). The consequences associated with patient no-shows are well documented, with literature demonstrating its detrimental impacts at the individual, organizational, and societal level (Marbouh et al., 2020; Toffaha et al., 2025). Existing estimates suggest that no-show rates can vary widely, ranging from 4% to 80% amongst organizations (Marbouh et al., 2020; Set et al., 2022). While certain demographic characteristics such as low socioeconomic status, public health insurance coverage, and young adults have been associated with higher incidence of nonattendance, absenteeism is a complex problem stemming from a multitude of factors (Dantas et al., 2018; Toffaha et al., 2025).

Although identifying the precise cause of no-shows can be challenging, the consequences are evident, with frequent absences being linked to negative health outcomes. For instance, those who frequently miss appointments have a 1.24 increased risk for poor health and are more susceptible to chronic conditions such as diabetes (Chapman et al., 2022; Leibner et al., 2023; Marbouh et al., 2020). Furthermore, absenteeism directly harms patients by delaying diagnosis and treatment leading to a disjointed care process. Patient harm also occurs by way of indirect consequences, with no-shows reducing availability, adding to wait times, and limiting resources. Studies demonstrate that persons with a high frequency of absences are also more likely to utilize emergency departments and inpatient services, further contributing to disruptions in health operations and resource allocation (Marbouh et al., 2020; Toffaha et al., 2025).

In addition to these clinical implications, nonattendance results in significant financial cost and operational inefficiencies. Missed appointments cause scheduling gaps, resulting in underutilization of provider skills and necessitating additional staff time to address downstream effects. Nationally, absenteeism is estimated to cost approximately $150 billion annually (Toffaha et al., 2025).

At the Community Health Care Center (CHCC), these challenges are magnified because the patient population served at this site possess characteristics that have been linked with higher levels of nonattendance (e.g., low socioeconomic, public health insurance). Moreover, individuals receiving psychiatric care are more likely to miss appointments compared to those in other specialties (Amagai et al., 2024; Mitchell & Selmes, 2007). As an organization that primarily provides mental health services, this makes CHCC particularly vulnerable to higher no-show rates. Currently, the no-show rate at CHCC is approximately 20%. While this may be favorable compared to the upper range of national estimates, it nevertheless contributes to system inefficiency and reduces access to care. Considering the persistent and multifactorial nature of no-shows, complete eradication may not be a realistic objective. However, implementation of a contextually appropriate, evidence-based intervention tailored to the needs of CHCC's patient population is warranted on account of its clinical and organizational significance.

Search Strategy

The data gathering process involved a comprehensive review of the electronic databases Pubmed and Google Scholar for available literature regarding causes of absenteeism and interventions aimed at addressing patient no-shows within the past ten years. Both backward and forward citation strategies were used to expand the scope of search results. Initially, research pertaining to psychiatric and mental health populations was preferred, however, due to limited search results with this requirement in place, the search process was expanded to include general settings and populations. Furthermore, studies evaluating the efficacy of interventions which contradicted the mission of the site (e.g. imposing financial or dismissal repercussions) were excluded.

Available Knowledge

To address the issue of no-shows, it is important to understand the factors that contribute to it. Current research indicates that the cause of nonattendance is complex and multifactorial in nature (Dantas et al., 2018; Toffaha et al., 2025; Valero-Bover et al., 2022). Despite its complexity, explanations for missed appointments can largely be grouped into three categories: patient-related factors, appointment-related factors and patient perspectives. Patient-related factors more strongly associated with an increased probability of missed appointments include demographic characteristics such as younger age, minority status and lower socioeconomic status. Less definitive patient factors attributing to no-shows include educational attainment, gender, and marital status (Dantas et al., 2018; Valero-Bover et al., 2022).

Appointment characteristics also influence attendance, with higher rates of no-shows occurring on Mondays and Fridays (Dantas et al., 2018). Additionally, lead time which is defined as the interval between when an appointment is scheduled and when it takes place has also been identified as a major contributor to nonattendance (Dantas et al., 2018; Milicevic et al., 2020; Valero-Bover et al., 2022).

Patient perspectives further contribute to missed appointments, as patients frequently report that their decisions to miss visits are driven primarily by their personal assessment of their own health. Other commonly cited patient factors include perceived quality of care, prior negative experiences, competing demands, and system insufficiencies (Chapman et al., 2022; Lindsay et al., 2024). This pattern can best be observed by the tendency for individuals to forgo health services when symptoms are manageable or do not interfere with daily functioning.

Given the multifactorial nature of no-shows, researchers have explored numerous interventions aimed at addressing this issue. Although various strategies have been investigated, the existing literature remains disproportionally focused on reminder systems with relatively few studies evaluating alternative interventions. These alternatives include behavioral economic interventions, patient contracts, combined strategy interventions, and transportation assistance (Crable et al., 2021; Werner et al., 2023).

Of these, incentive-based change efforts were the only initiative to demonstrate modest efficacy with the remaining efforts not demonstrating substantial benefits. In contrast, reminder systems have consistently demonstrated their efficacy across numerous studies (Milicevic et al., 2020; Oikonomidi et al., 2023; Shah et al., 2016; Tarabichi et al., 2023; Ulloa-Pérez et al., 2022; Valero-Bover et al., 2022; Werner et al., 2023). Quality improvement projects conducted by Clouse et al., (2017) and Boyle and Schwinck (2022) further support this conclusion. Those interventions included the use of reminder calls, motivational interviewing, and patient education, resulting in reductions of no-shows by 7% and 55% . One possible explanation for the effectiveness of reminder-based strategies is that forgetfulness is frequently cited as a primary reason for missed appointments, and as such reminders maybe more fruitful since they can directly address one of the most common causes of nonattendance.

Building on the demonstrated effectiveness of reminder systems, some studies also explored the utility of predictive modeling approaches to more effectively address outreach by identifying patients at elevated risk of nonattendance. Studies employing such approaches were able to exhibit reductions in no-shows of 3.7%, 7% -25% and 40 – 50% respectively (Chong et al., 2020; Oikonomidi et al., 2023; Ulloa-Pérez et al., 2022; Valero-Bover et al., 2022). These models also showed strong predictive accuracy with specificity ranging between 69% – 78 % (Chong et al., 2020; Valero-Bover et al., 2022). Moreover, the predictive frameworks utilized in some of these reports were able to identify individuals at risk of nonattendance 2.34 times more accurately than chance alone (Milicevic et al., 2020).

However, as previously noted, not all studies reached the same conclusion with one study determining that reminder calls were not an effective intervention (Oikonomidi et al., 2023). Additionally, one review found that universal (non-targeted) reminders perform at least as well as targeted, predictive model–based outreach, and another study reported that inclusion of a brief pre-admission telephone reminder did not reduce no-show rates (Crable et al., 2021; Gallefoss et al., 2022). While findings regarding causes and solutions for absenteeism differed, no-show history consistently emerged as a strong predictor of future missed appointments amongst all studies. Thus, even though the variables included in predictive model interventions varied, nearly all of them incorporated prior no-show history because of its strong and consistent association with attendance.

Rational

This project was guided by Lewin's theory of change (LTC) which was originally formulated in the 1940's by Kurt Lewin. His paradigm proposes a three-stage model of change consisting of unfreezing, moving and refreezing. Practical application of this framework involves identifying the reasons a problem persists, constructing a plan aimed at addressing contributing variables, and reinforcing the change to maintain improvement (Burnes, 2020). Applying this model to our scenario, a root cause analysis was conducted to identify factors contributing to no-shows within the organization (Appendix A). The evaluation demonstrated that no-show rates are influenced by organizational factors (e.g., no educational materials), staffing issues (e.g., limited training), and cultural perspectives (e.g., normalization of missed appointments). While each factor adds to the problem, the absence of a high-risk patient outreach process emerged as a significant gap. Existing literature has consistently shown that high-risk patients are the most likely to miss appointments and conducting outreach targeted towards individuals who have historically exhibited these behaviors is one of the most effective and feasible ways to reduce patient no-shows.

The rational guiding this initiative is based on the notion that constructing a standardized outreach process targeting high-risk patients will lead to improved engagement, heightened adherence, and enhanced continuity of care with the intention of ultimately reducing absenteeism amongst individuals. The implementation will be guided by the Institute for Healthcare Improvement's (IHI) Model for Improvement, which emphasizes small-scale testing before broader application (Institute for Healthcare improvement, n.d). This approach is expected to increase the likelihood of success by allowing for continuous evaluation, adaptation, and refinement of the intervention as it is introduced (Institute for Healthcare improvement, n.d).

Specific Aims Statement

At the conclusion of the implementation period, targeted outreach will be conducted for all patients deemed high-risk on the pilot nurse practitioner's panel. This in turn will lead to a reduction in patient no-show rates by 5% amongst patients scheduled with the pilot nurse practitioner by the end of the intervention period.

Methods

Context

CHCC is an outpatient primary care center and mental health clinic located in an urban setting which serves low-income adults. Patients served at this location are aged between 18 – 80 years old and are primarily Caucasian. Insurance providers for patients are a mix of private and public insurance, with 98% of patients having some form of public insurance. While the health center offers primary healthcare services, the organization predominantly delivers behavioral and mental healthcare. Mental health services are provided via a team-based approach with teams being comprised of a nurse, case manager, therapist, and licensed medical provider. Supportive employment and housing specialists may be involved if certain conditions are met. Currently there are 3 LMPs, 6 therapists and one nurse.

Presently, the clinic employs an automated reminder system which contacts patients on multiple occasions (one week before appointment, one day before appointment, and day of appointment) based on their preference in the form of a text message, phone call or both. As of June, a care coordinator position was established to complete outreach to patients who have been disengaged from therapy or treatment for a minimum of three months. This process involves therapists identifying disengaged patients and providing this information to the care coordinator, who then initiates an outreach call. If the patient does not answer their phone on the initial call, another call will be made in two weeks, and a final follow-up call will be made two weeks after the second failed attempt. If the patient has not responded after this time, a discharge letter will be sent and their file will be closed if no further contact is made. This position is in its infancy, therefore, no standardized process currently exists for care coordinators to follow in completing this objective. The aforementioned model reflects the practices of the care coordinator at this specific location rather than across the entire organization. Additionally, current outreach efforts by care coordinators are directed toward therapy patients only, and do not extend to psychiatric services. Consequently, this further illustrates the importance of the current project as it may assist the organization in establishing a standardized and effective outreach process that can be applied consistently across departments.

Interventions

This quality improvement (QI) project aimed to implement an outreach process targeted towards patients at an elevated risk for missing appointments utilizing a simplified predictive modeling approach based on their historical no-show patterns. Patients being seen by the pilot nurse practitioner were categorized as high-risk if they missed 25% or more of their scheduled appointments. The data was obtained from Epics scheduling system which automatically calculated patients' no-show percentages based on attendance history. The initial intervention and corresponding Plan-Do-Study-Act (PDSA) cycle was completed over the course of four weeks. After assessing and refining the interventions, a second and final PDSA cycle was carried out.

At the start of each week, the nurse practitioner student reviewed the following week's appointments to determine if the scheduled patients were at high or low risk of nonattendance and constructed a corresponding list of those requiring outreach. Targeted outreach was then completed by the nurse practitioner student in the form of a guided telephone call (Appendix B). Prior to completing outreach, the nurse practitioner student consulted with clinical preceptor to ensure each patient was appropriate for non-urgent contact. During the call, patients were reminded of their upcoming appointment and asked if they planned to attend. If they could not attend their appointment, patients were given the option to reschedule their appointment or convert it to virtual if necessary. Patients were called twice, if they were not reached by the second attempt, no additional attempts were made and outcomes were documented. If the number was incorrect, it was tracked and an alternate contact method was attempted. Detailed process steps can be found (Appendix C).

For improved accuracy the attendance spreadsheet was filtered for appointment types that did not provide clear attendance data or if the appointment in question did not represent a true patient visit. This resulted in exclusion of the following appointment types: canceled, history, letter out, refill, order only, and my chart encounter. Thus, appointment types which were ultimately incorporated included appointment, behavioral health visits and mental health visits. This process was employed to obtain overall no-show rates for the clinic, and the pre- and post- no-show rates for the piolet NP.

Study of the interventions

To assess the effectiveness of the intervention retrospective data was used to establish a baseline. No-show rates obtained during the intervention period were then compared to baseline no-show rates to understand if observed improvements were attributable to the intervention. Descriptive statistics were then used to examine overall trends, and a chi-square test was conducted to assess whether differences in no-show rates were statistically significant. Additionally, the number of patients successfully reached by phone and the outcomes of those interactions was tracked (e.g., unable to contact, cancellations, rescheduling) to provide further insight into the intervention's impact and efficiency.

Measures

Balancing measures included detailed time logs tracking the amount of time spent calling, identifying, and speaking with patients to estimate the cost associated with implementing this intervention. The primary measure was no-show rates since this is the central aim of the intervention. To calculate this metric the number of missed appointments was divided by the total number of scheduled appointments during the intervention period. Process measures involved calculating the number of high-risk patients that were successfully contacted and barriers to contact.

Analysis

Quantitative data analysis was used to compare no-show rates before and after the implementation of the predictive model and targeted outreach. Descriptive statistics summarized baseline and post-intervention no-show rates. A chi-square test was used to assess whether the difference in no-show rates was statistically significant and run charts were used to display trends over time. Process measures, including the percentage of high-risk patients identified and successfully contacted was analyzed to assess implementation fidelity. All analyses were conducted using SPSS. Furthermore, the accuracy of the predictive model was calculated by assessing retrospective appointment data by determining how many of the patients identified as high-risk actually missed their appointments. The sensitivity and specificity was also calculated to understand how well the model was able to identify no-shows.

Ethical considerations

The OHSU IRB has determined that this is not research. Nevertheless this initiative considered the sensitivity of patient information, vulnerability of patients, and subsequently ensured that patient data was safeguarded and no harm was bestowed upon individuals. Data analyzed was deidentified to guarantee privacy. All PHI was handled in accordance with HIPPA guidelines and in compliance with the community health center standards and procedures. To ensure safety, the pilot PMHNP was consulted to determine appropriateness of patients for the intervention. On going evaluation was completed to ensure high standards of care, safety and privacy.

Results

Predictive Model Performance and Temporal Validation

The predictive model's ability to correctly identify high-risk appointments was evaluated using both retrospective scheduling data and prospective data obtained during the intervention period. Retrospective scheduling data from August 10 to October 10 consisted of a total of 103 appointments, of which 84 were completed and 19 (18.4%) were NS. Eighteen appointments were classified as high-risk by the model. Of these, 8 patients did not show (true positive) and 10 attended despite being identified as at an elevated risk (false positives). Conversely, of the patients who were not flagged, 11 were no-shows (false negatives) and 74 attended their appointments as expected (true negatives). Overall, these results correspond to a sensitivity of 42% and specificity of 88% (Appendix D, Table 1).

Prospective scheduling data obtained during the intervention included 68 appointments with 17 being characterized as high-risk. Among these high-risk appointments, 11 resulted in no-shows (true positives) and 6 were completed in spite of being flagged as high risk (false positives). For patients not designated as high-risk, 13 no-showed (false negatives) and 38 attended as anticipated (true negatives). In total, these outcomes correspond with a sensitivity of 46% and a specificity of 86% (Appendix D, Table 2).

Implementation and PDSA cycles

The project was carried out over the course of two distinct PDSA cycles (PDSA 1 and PDSA 2) to incorporate any refinements identified in the initial implementation phase (PDSA cycle 1) into the subsequent cycle (PDSA 2). PDSA cycle 1 was conducted from October 10 to November 17 and PDSA cycle 2 was completed from November 17 to November 24, with the primary difference between the two cycles being the threshold necessary for patients to be classified as high-risk. In PDSA cycle 1, patients were distinguished as high-risk if they had a no-show history of ≥25%. Whereas, in PDSA cycle 2 the high-risk threshold was lowered to a no-show history of ≥15% to increase the proportion of patients classified as high-risk and eligible for outreach.

No-Show Rates

During PDSA cycle 1, 42 appointments were scheduled, of which 10 patients (23.9%) met high-risk criteria and received outreach attempts. Sixteen of the 42 appointments (38.1%) resulted in no-shows. In PDSA cycle 2, there were a total of 26 appointments scheduled with eight (30.8%) meeting high-risk criteria and receiving outreach attempts. A total of eight (30.8%) of the 26 patients scheduled during this time frame no-showed.

Taken together, this equates to a total of 68 appointments scheduled during the implementation period with 24 (35.3%) patients missing their appointment. Compared to baseline no-show rate of 18.4%, this represents a relative risk of 1.91, meaning that patients were twice as likely not to show during the implementation period (Appendix E, Table 1; Figure 1). A chi-square analysis of independence found that this difference was statistically significant ($x^2(1, N = 171) = 6.18$ $p = 0.013$.)

Process measure

Calls were attempted for all high-risk patients (n=17) with contact being successfully achieved for 6 patients (35.% reach). Of the patients that were contacted, the script was successfully utilized in 4 cases. Barriers to contact included incorrect phone numbers being listed on the patient's profile (n=2), inability to contact alternate due to absence of release of information (n=4), and technical difficulties (n=1).

Balancing measures

The time needed to calculate no-show risk and complete outreach was monitored as a balancing measure. During PDSA cycle 1 an average of 22 minutes per clinical day was required to complete quality improvement related outreach for one day's worth of patients on the pilot nurse practitioner's schedule. Whereas the time necessary to complete these activities during PDSA cycle 2, increased to 31. 6 minutes per clinical day.

Discussion

This quality improvement project attempted to reduce patient no-show rates in an outpatient psychiatric facility by identifying patients at an elevated risk of missing appointments using historic attendance patterns and then conducting outreach to those meeting high-risk criteria. The project did not improve no-show rates compared to baseline values, with no-show rates increasing from 18.4% pre-intervention to 35.3% post-intervention, a statistically significant change at the $p<0.05$ level.

Processes measures indicate high implementation fidelity, and outreach calls were attempted for all high-risk patients. However, successful contact was only achieved for 35% of patients, with several system barriers such as incorrect phone numbers, lack of release of information for alternate contact and technical difficulties likely reducing engagement, outreach and the interventions potential impact.

While Clouse et al (2017) were able to observe a reduction in no-show rates by 7 percentage points after implementing their nurse-initiated telephone call initiative, contextual differences likely explain the variation in results between their project and the current project. In their setting, no formal reminder or engagement protocol appeared to be in place prior to implementation. Thus, the improvements they observed may largely stem from the general benefit associated with the introduction of reminders rather than a direct effect of the intervention itself. By comparison, the current clinical site already employs an automated reminder system, meaning any added benefit of additional outreach may have had a smaller observable impact.

Additionally, variations in outreach strategy may further explain the observed differences in outcomes between the studies. Clouse et al (2017) provided outreach to all scheduled patients, whereas this project utilized targeted outreach based on no-show risk. The reduction seen in PDSA cycle 2 of the current study which expanded the proportion of patients receiving outreach and resulted in a decrease of 8-percentage points in no-show rates between PDSA cycle 1 and PDSA cycle 2 suggests that migrating towards a non-targeted outreach process may be more effective than targeted models. This pattern is consistent with Oikonomidis et al. (2022), who reported that non-targeted reminders reliably reduce no-show rates, while evidence for additional benefit from targeted, predictive-model–based outreach remains uncertain.

Although a non-targeted outreach strategy may improve no-shows as suggested by Clouse et al (2017) and Oikonomidis et al. (2022), it may not be a feasible option for all health care settings. As shown in Appendix F, even a targeted outreach initiative such as the one conducted in this project can result in unintended financial consequences, increased workload and higher cost without providing an additional benefit. Although such costs might theoretically be offset by improved attendance, these costs would likely be greater if employing a fully non-targeted model. Considering that many healthcare settings do not possess the resources or infrastructure (automated reminder systems) necessary to implement universal outreach, such an approach may not be practical for all clinics. This highlights the importance of designing QI interventions that take into account site specific workflows, resources and constraints.

An assessment of the model's performance exhibited a modest ability to identify patients at an elevated risk of nonattendance, with sensitivity scores ranging from 42%- 46% and a specificity of 86%-88%. This performance was lower than that reported in studies whose model was able to correctly identify no-shows approximately 83% of the time (Liu et al., 2022). In comparison to other studies that used more complex multivariable predictive models involving factors such as insurance status and diagnosis, the current model utilized simplified predictive approach based solely on prior no-show history (Chong et al., 2020; Liu et al., 2022). This design was intentionally selected because prior no-show history was found to be a strong predictor of absenteeism across multiple studies while simultaneously minimizing additional administrative burden or cost associated with complex models. The difference in variables included may therefore explain the difference in sensitivity between the models described in the available literature and that of the current model for which low sensitivity likely negatively influenced the effectiveness of the intervention overall.

Limitations

Several limitations exist and should be considered. As illustrated in Appendix G, weeks with five missed appointments occurred in both the intervention and pre-intervention phase, with the highest number of missed appointments being six during the intervention period. Although chi-squre analysis found a statistically significant difference between these periods, the number of missed appointments per week did not drastically differ from the clinician's typical range (Appendix G). This indicates that the observed change may represent a typical pattern in no-shows for the clinic rather than an effect of the intervention. This finding may also signal that the time frame utilized was likely not sufficient to fully capture the true no-show pattern of the clinic and clinician. Additionally, the retrospective data used for comparison were obtained recently and were not matched to the same seasonal timeframe from the prior year. As a result, seasonal factors such as holidays, weather conditions, and fluctuations in patient demand may have influenced outcomes independently of the intervention.

Lastly, scheduling and documentation inconsistencies within the clinical sites electronic health record (EHR) may have affected the accuracy of outcome measures. During data review, some appointments that were manually recorded as missed visits were not captured as no-show within the EHR. This discrepancy suggests that certain missed visits may not have been consistently classified by the system or front desk staff, introducing the potential for misclassification bias. While multiple factors could have contributed to this discrepancy, one possible explanation is the improper classification of same-day cancellations. In such instances, visits may have been labeled as a cancellation rather than a no-show event either due to human error or because of how appointment outcomes were entered into the EHR.

Ultimately, the limitations within this study highlight the necessity for future studies to employ larger samples, longer observation periods and standardized scheduling documentation practices to improve the reliability and generalizability of findings.

Conclusion

Overall, the current single variable predictive based model is insufficient for reliably identifying patients at an elevated risk for missing appointments and the quality improvement project as originally designed is not an effective strategy for addressing this problem. In addition to suboptimal model performance, the intervention was also affected by implementation barriers that likely reduced its potential impact. Although calls were attempted for all high-risk patients, successful contact was only achieved 35% of the time. As a result, even if a patient was properly identified as high-risk, the low likelihood of successful contact limited the initiative's overall ability to meaningfully influence attendance behavior. These findings suggest that in the current clinical setting the primary opportunity for improvement may lie in enhancing patient reach and communication processes, rather than constructing a simplified risk stratification tool. Therefore, future research should focus on exploring strategies to improve successful patient contact and outreach effectiveness.

References

Amagai, S., Vonesh, E., Adams, J., & Luo, Y. (2024). Closing the gap: Addressing telehealth disparities across specialties in the sustained pandemic era. *Npj Digital Medicine*, *7*(1), 217. https://doi.org/10.1038/s41746-024-01201-w

Boyle, M. K., & Schwinck, J. (2022). Reducing missed psychotherapy appointments: An advanced practice nurse-initiated telephone orientation protocol. *Perspectives in Psychiatric Care*, *58*(4), 2756–2763. https://doi.org/10.1111/ppc.13116

Burnes, B. (2020). The Origins of Lewin's three-step model of change. *The Journal of Applied Behavioral Science*, *56*(1), 32–59. https://doi.org/10.1177/0021886319892685

Chapman, K. A., Machado, S. S., Van Der Merwe, K., Bryson, A., & Smith, D. (2022). Exploring primary care non-attendance: A study of low-income patients. *Journal of Primary Care & Community Health*, *13*, 21501319221082352. https://doi.org/10.1177/21501319221082352

Chong, L. R., Tsai, K. T., Lee, L. L., Foo, S. G., & Chang, P. C. (2020). Artificial intelligence predictive analytics in the management of outpatient MRI appointment no-shows. *American Journal of Roentgenology*, *215*(5), 1155–1162. https://doi.org/10.2214/AJR.19.22594

Clouse, K. M., Williams, K. A., & Harmon, J. M. (2017). Improving the no-show rate of new patients in outpatient psychiatric practice: An advance practice nurse-Initiated telephone engagement protocol quality improvement project. *Perspectives in Psychiatric Care*, *53*(2), 127–134. https://doi.org/10.1111/ppc.12146

Crable, E. L., Biancarelli, D. L., Aurora, M., Drainoni, M., & Walkey, A. J. (2021). Interventions to increase appointment attendance in safety net health centers: A systematic review and meta-analysis. *Journal of Evaluation in Clinical Practice*, *27*(4), 965–975. https://doi.org/10.1111/jep.13496

Dantas, L. F., Fleck, J. L., Cyrino Oliveira, F. L., & Hamacher, S. (2018). No-shows in appointment scheduling: A systematic literature review. *Health Policy*, *122*(4), 412–421. https://doi.org/10.1016/j.healthpol.2018.02.002

Gallefoss, L. J., Gabrielsen, K. B., Haugland, S. H., Clausen, T., & Vederhus, J.-K. (2022). Effects of a brief pre-admission telephone reminder on no-show and dropout rates in substance use disorder treatment: A quasi-experimental study. *Substance Abuse Treatment, Prevention, and Policy*, *17*(1), 61. https://doi.org/10.1186/s13011-022-00489-9

Institute for Healthcare Improvement. (n.d.). *Model for improvement*. https://www.ihi.org/library/model-for-improvement

Leibner, G., Brammli-Greenberg, S., Mendlovic, J., & Israeli, A. (2023). To charge or not to charge: Reducing patient no-show. *Israel Journal of Health Policy Research*, *12*(1), 27. https://doi.org/10.1186/s13584-023-00575-8

Lindsay, C., Baruffati, D., Mackenzie, M., Ellis, D. A., Major, M., O'Donnell, C. A., Simpson, S. A., Williamson, A. E., & Wong, G. (2024). Understanding the causes of missingness in primary care: A realist review. *BMC Medicine*, *22*(1). https://doi.org/10.1186/s12916-024-03456-2

Liu, D., Shin, W.-Y., Sprecher, E., Conroy, K., Santiago, O., Wachtel, G., & Santillana, M. (2022). Machine learning approaches to predicting no-shows in pediatric medical appointment. *Npj Digital Medicine*, *5*(1), 50. https://doi.org/10.1038/s41746-022-00594-w

Marbouh, D., Khaleel, I., Al Shanqiti, K., Al Tamimi, M., Simsekler, M. C. E., Ellahham, S., Alibazoglu, D., & Alibazoglu, H. (2020). Evaluating the impact of patient no-shows on service quality. *Risk Management and Healthcare Policy*, *Volume 13*, 509–517. https://doi.org/10.2147/RMHP.S232114

Milicevic, A. S., Mitsantisuk, K., Tjader, A., Vargas, D. L., Hubert, T. L., & Scott, B. (2020). Modeling patient no-Show history and predicting future appointment behavior at the Veterans Administration's outpatient mental health clinics: NIRMO-2. *Military Medicine*, *185*(7–8), e988–e994. https://doi.org/10.1093/milmed/usaa095

Mitchell, A. J., & Selmes, T. (2007). Why don't patients attend their appointments? Maintaining engagement with psychiatric services. *Advances in Psychiatric Treatment*, *13*(6), 423–434. https://doi.org/10.1192/apt.bp.106.003202

Oikonomidi, T., Norman, G., McGarrigle, L., Stokes, J., Van Der Veer, S. N., & Dowding, D. (2023). Predictive model-based interventions to reduce outpatient no-shows: A rapid systematic review. *Journal of the American Medical Informatics Association*, *30*(3), 559–569. https://doi.org/10.1093/jamia/ocac242

Set, K. K., Bailey, J., & Kumar, G. (2022). Reduction of no-show rate for new patients in a pediatric neurology clinic. *The Joint Commission Journal on Quality and Patient Safety*, *48*(12), 674–681. https://doi.org/10.1016/j.jcjq.2022.09.001

Shah, S. J., Cronin, P., Hong, C. S., Hwang, A. S., Ashburner, J. M., Bearnot, B. I., Richardson, C. A., Fosburgh, B. W., & Kimball, A. B. (2016). Targeted reminder ohone calls to patients at high risk of no-show for primary care appointment: A randomized trial. *Journal of General Internal Medicine*, *31*(12), 1460–1466. https://doi.org/10.1007/s11606-016-3813-0

Tarabichi, Y., Higginbotham, J., Riley, N., Kaelber, D. C., & Watts, B. (2023). Reducing disparities in no Show rates using predictive model-driven live appointment reminders for at-risk patients: A randomized controlled quality improvement initiative. *Journal of General Internal Medicine*, *38*(13), 2921–2927. https://doi.org/10.1007/s11606-023-08209-0

Toffaha, K. M., Simsekler, M. C. E., Omar, M. A., & ElKebbi, I. (2025). Predicting patient no-shows using machine learning: A comprehensive review and future research agenda. *Intelligence-Based Medicine*, *11*, 100229. https://doi.org/10.1016/j.ibmed.2025.100229

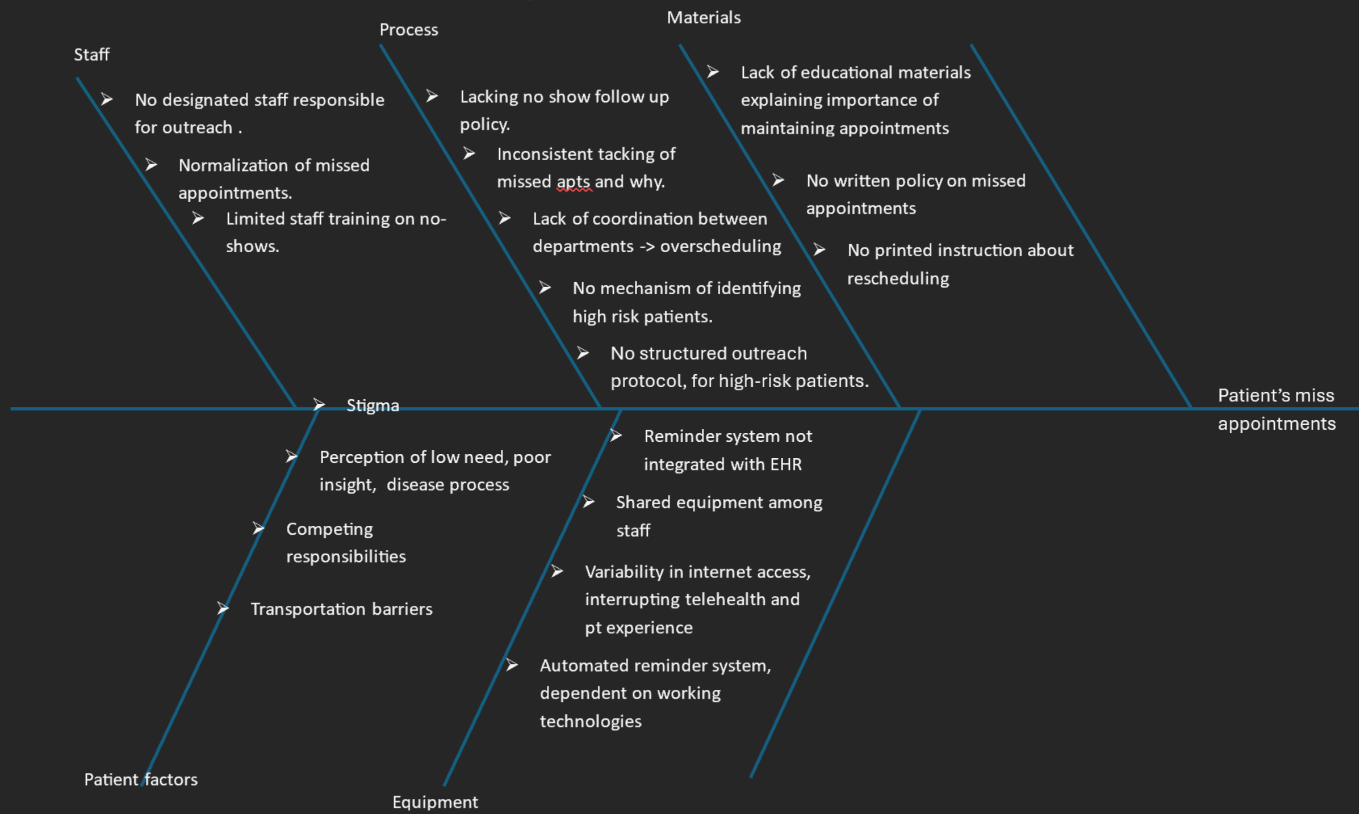
Ulloa-Pérez, E., Blasi, P. R., Westbrook, E. O., Lozano, P., Coleman, K. F., & Coley, R. Y. (2022). Pragmatic randomized study of targeted text message reminders to reduce missed clinic visits. *The Permanente Journal*, *26*(1), 64–72. https://doi.org/10.7812/TPP/21.078

Valero-Bover, D., González, P., Carot-Sans, G., Cano, I., Saura, P., Otermin, P., Garcia, C., Gálvez, M., Lupiáñez-Villanueva, F., & Piera-Jiménez, J. (2022). Reducing non-attendance in outpatient appointments: Predictive model development, validation, and clinical assessment. *BMC Health Services Research*, *22*(1). https://doi.org/10.1186/s12913-022-07865-y

Werner, K., Alsuhaibani, S. A., Alsukait, R. F., Alshehri, R., Herbst, C. H., Alhajji, M., & Lin, T. K. (2023). Behavioural economic interventions to reduce health care appointment non-attendance: A systematic review and meta-analysis. *BMC Health Services Research*, *23*(1). https://doi.org/10.1186/s12913-023-10059-9

Appendix A

Cause and Effect – Root Cause Analysis



Appendix B

Script

- Pre call checklist:
    - Confirm phone number, preferred language, arrange for interpreter if needed
    - Gather appointment details prior to call (i.e date, time, location, clinician)
    - Have spread sheet ready to gather data i.e barriers, responses
- Introduction:
    - Hi, this is a psychiatric nurse practitioner student (student name) working with (preceptors name) calling for (patients first and last name), before we discuss, I need to verify your identity. Can you please confirm your full name and date of birth?
- Supportive framing:
    - I am calling because you have an appointment on (date, time) with (clinician, service) and my goal is to make it as easy as possible to ensure you are able to make it to your appointment.
- Assess Confidence:
    - How confident that you are able to make it to your appointment on a scale of zero to ten?
- Barriers:
    - Is anything preventing you from able to making it in such as transportation or child care?
- Problem solve:
    - Refer to appropriate individuals, scheduling to switch to virtual or moving of dates
- Rescheduling
    - Thank you for informing me that you would like to reschedule your appointment, unfortunately I do not have the credentials to make that change. However, I will pass your message along to our scheduling team and you should see a corresponding adjustment once I have been able to relay that message.
- Confirmation of scheduling plan
    - Just to summarize your date is on (date, time) with (provider name, service)
- Conclusion:
    - Thank you for your time, if anything changes please call (clinic phone) so we can make any necessary adjustments.

Appendix C

Process

- ***No show rates***: Obtain current no-show rates to identify the pre-intervention level from data analytic group at health care organization.
- ***High risk definition:*** a patient who has a percentage of missing 25% or more of all scheduled appointments.
- ***Data source:*** Patient no-show percentages will be extracted from Epic's scheduling system, which automatically calculates the proportion of missed appointments for each patient based on documented attendance history.
- ***Application*****:** predictive model will be used prospectively to identify patients considered high risk one week prior to their scheduled appointment, at which point targeted outreach will be completed.
- ***Targeted outreach:*** Patients tagged as high risk will receive a standardized phone call from the Nurse Practitioner student.
- ***Appropriateness (safety):*** before outreach, a confirmation with the preceptor regarding if the patient is clinically appropriate for a non-urgent call, and if requested by the patient they are safe to adjust appointment times or switch to virtual appointment.
- ***Voicemail:*** a patient will be called two times, before being deemed unreachable at which point no more attempts will be made. This will be recorded for tacking information and further analysis.
- ***Wrong number:*** mark as wrong number in chart, attempt alternate contact if available. This will be recorded for further analysis.
- ***Data tracking:*** after the appointment date passes, actual attendance outcomes will be recorded
    - ***High risk:*** Amount which attended and no-showed .
    - ***Low risk (control):*** Amount which attended and no-showed.
- ***Low-risk (control) patients:*** Patients who do not meet high- risk criteria will not receive additional outreach beyond standard reminders.
- ***One month review:*** after 1 month of initiating quality improvement project a PDSA review will be conducted to identify changes that could enhance efficiency and effectiveness of intervention.
- ***Final Analysis:*** At project completion a comparison between the outcomes obtained pre and post intervention will be completed across PDSA cycle 1and 2:
    - Overall no show-rate pre vs post
    - High-risk subgroup vs low risk no-show rate pre vs post
    - Model sensitivity/specificity changes if model parameters are adjusted in PDSA cycles.
- ***Dissemination:*** Distribution of findings will occur via PowerPoint presentation, along with PDF files of the studies evaluated during the review of available literature.

Appendix D

Table 1

Retrospective Confusion matrix

	No- show	Show	Total
Predicted No-Show	8 (TP)	10 (FP)	18
Predicted Show	11 (FN)	74 (TN)	85
Total	19	84	103

Table 2

Temporal Validation Confusion matrix

	No-show	Show	Total
Predicted No-show	11 (TP)	6 (FP)	17
Predicted show	13 (FN)	38 (TN)	51
Total	24	44	68

Appendix E

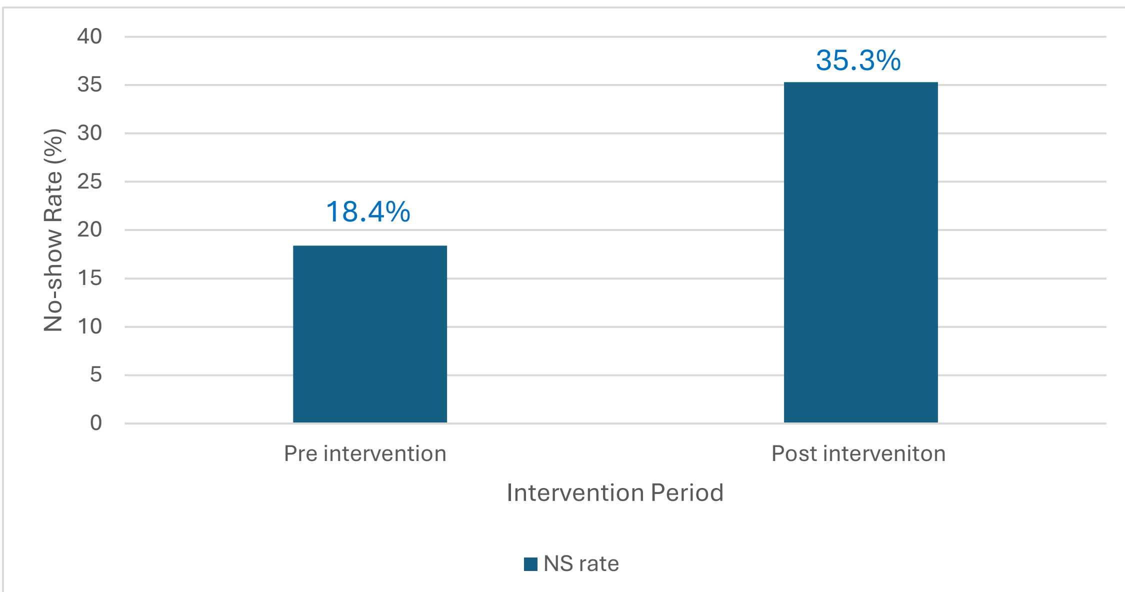
Table 1

Pre- and post- No-Show Rates

Period	Completed (n)	No-show (n)	Total (n)	No-show rate (%)
Per-intervention	84	19	103	18.4%
Post-intervention	44	24	68	35.3%

Figure 1

No-Show Rates Before and After Intervention



Appendix F

Table 1

Estimated Labor Costs and Financial Impact of Outreach Activities

Measure	Value	Calculation	Estimated Cost
Time per day for QI (PDSA 1)	22 minutes	___	___
Time per day for QI (PDSA 2)	32 minutes	___	___
Estimated receptionist wage	22/hr	___	___
Daily labor cost	___	32min/60min x $22	$10.34/day
Weekly QI labor cost (provider with 2 clinical days)	___	$10.34 x 2	20.68/week
Annual QI labor cost (provider with 2 clinical days)	___	20.68 x 52	≈1,200/year
Annual QI labor cost (provider with 5 clinical days)	___	10.34 x 5 x 52	≈2,688/year
Average reimbursement per visit	$143	___	___
Increase in no-show rate	16.9 percentage points	___	___
Missed visits per week	~2 visits	___	___
Weekly revenue loss	___	2 x $143	≈ $300/week
Annual revenue loss	___	$300 x 52	≈ 15,000/year

Appendix G

Figure 1

Number of No-Shows per Week