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RESEARCH ARTICLE

IMPROVING PATIENT FLOW IN THE OUTPATIENT CLINIC

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ABSTRACT

Rationale, aims and objectives: Improving patient flow increases patient safety, improves clinical outcomes, positively impacts patient and staff satisfaction, and increases revenue. Factors contributing to lengthy waiting times for patients include long registration processes, obtaining laboratory results, preparation of chemotherapeutic agents, adequacy of human resources, and physical capacity meeting patient volumes. We aimed to study and test changes that would decrease waiting times at the Barbara Ann Karmanos Cancer Institute (KCI) Wertz Outpatient Clinic by at least 20% by the end of the 12-month study period (April 15, 2012 to April 15, 2013), without incurring extra cost or resource burden.

Method: We used the IHI Model for Improvement to identify bottlenecks to develop and test changes for implementation. We estimated the mean and standard deviation (SD) of patient transit times, both before and after implementing an intervention(s).

Results: At baseline, patients' mean total transit time (TTT) was 139.5 minutes. After intervention 1, (a different set of 19) patients' mean TTT was 131.1 minutes, a reduction of 8.4 minutes or 6.0%. The implementation of intervention 1 was the addition of 5 minutes to normal appointment times allocated for seeing the oncologist. A second intervention was planned but not executed in time during the study period.

Conclusion: A mean reduction of 6% may not be of large benefit per an individual patient. However, such a reduction may be worthwhile from a clinic operations improvement standpoint. There were limitations to this pilot study, which present as areas for improvement in further study.

INTRODUCTION

Improving patient flow through the hospital increases patient safety, improves clinical outcomes, positively impacts patient and staff satisfaction, and increases revenue (1, 2). Improving flow requires multidisciplinary core team leadership with participation from staff working in the initial area of focus, as well as staff who have a cross-organizational view of the flow in the given system (1-3). Patient flow has been an area of focus for the Institute for Healthcare Improvement (IHI), which has worked with more than 60 hospitals in the United States and the United Kingdom to evaluate, develop, and implement methods for improving flow in hospitals, particularly in the emergency department, ICU, and surgical units. Outpatient oncology clinics, however, have so far eluded IHI publication in this field (3).

Studies of patient satisfaction in outpatient cancer clinics show that decreasing wait times frequently leads to overall improved patient satisfaction (4-6). Patients who spend longer periods of time waiting are less likely to recommend the facility and have lower ratings of overall care (7). Factors contributing to lengthy waiting times for patients and their families include long registration processes, obtaining laboratory results, preparation of chemotherapeutic agents, adequacy of human resources, and physical capacity meeting patient volumes (4). Simultaneously, the time spent with the physician is a stronger predictor of patient satisfaction than is the time spent in the waiting room, suggesting that shortening patient waiting times should not come at the expense of time spent with the provider (8).

A significant amount of literature focuses on the use of computer simulation of the queue process to optimize patient flow analysis and the allocation of resources to improve delivery of outpatient services. Special emphasis has been on appointment scheduling (9, 10). Specific to the cancer setting, Santibanez, et al. (11) propose improved patient flow through better appointment scheduling and examination room capacity and allocation. Sepulveda et al. (12, 13) analyzed patient flow throughout the unit, the impact of alternative floor layouts,

different scheduling options, and resource and patient-flow requirements for a new building.

Beyond data collection and computer simulation, Tyono, et al. (14) tested and implemented change to improve patient flow. They mapped chemo delivery to better understand the patient timeline and identified bottlenecks. Their model showed that temporal decoupling of chemo and clinic same-day visits, along with efficient utilization of chemo positions, nursing, and pharmacy time, significantly decreased in-system waits for chemo patients. Hendershot, et al. (15) performed the Express Chemotherapy Pilot, examining the length of the clinic visit in relation to the actual treatment time required. They implemented this fast tracking system after reallocating existing resources and establishing an autonomous nurse-run chemotherapy clinic, thus expediting care without affecting cost (4). Kallen et al. (16) interviewed the staff of a given chemotherapy unit to delineate and rank-order strategies for reducing patient wait time, then implemented a multi-faceted intervention plan because a series of changes, rather than a single change item, has been reported to be more effective in improving outcomes (10). They used an effective electronic measurement system to record appointment-related events for baseline and interventional phases.

Optimizing Patient Flow is part of a series of innovative programs developed by the IHI encouraging hospitals to improve the quality of care using the Model for Improvement for evaluating patient flow, testing changes for improvement, and measuring results (1, 2). The organizations most successful in implementing this model have made changes in these key areas: decreasing and smoothing variation; appropriately matching the available capacity in the system to meet the demand for care; better distributing the demand and improve the workflow rather than increase staff to handle the times of peak demand; and changing work environment to provide leverage for improvements in worker performance (1, 2). Departmental areas of focus include the flow of elective surgery, inpatient admissions through emergency departments, the intensive care unit to medical/surgical units, and inpatient setting to long-term-care facilities. These IHI reports do not strongly emphasize the outpatient oncology experience, yet offer great potential for increased cancer center clinic efficiency.

Objectives, Study Design and Methods

The aim was to study and test changes that will improve clinic efficiency in order to decrease waiting times of patients under the assigned care of an oncologist at the KCI Wertz Outpatient Clinic by at least 20% over a 12-mo. study period (April 15, 2012 to April 15, 2013), without incurring extra cost or resource burden.

We estimated the mean and standard deviation (SD) of patient transit time from signing in to the Wertz Laboratory to leaving the Wertz Outpatient Clinic, both before and after implementing an intervention(s) designed to reduce the total patient transit time. Intervention 1 was to add 5 minutes to normal appointment times allocated for seeing the oncologist to prevent overbooking and to allow for longer discussion. Specifically, the project involved 2 phases: 1) identify bottlenecks to develop changes, and 2) test prospective changes to decrease waiting times using the IHI Model for Improvement (1).

Patient eligibility criteria: 1) oncology patients evaluated at the Wertz Outpatient Cancer Clinic; 2) patients undergoing only lab and doctor visits; and 3) appointment days of Wednesday or Thursday, for study staff supervision reasons.

Data Collectors: Medical students were trained by the project author to observe and record a patient's arrival time at each clinic station on the Data Collection Form (see Figure 1).

Baseline Assessment and Intervention: We tested a change with the IHI Model for Improvement, which included Plan-Do-Study-Act (PDSA) cycles as follows:

Plan:

- Intervention Cohort 0: Establish baseline data to identify bottlenecks.
- Intervention Cohort 1: Suggest a change to test: add 5 minutes per patient visit with his/her oncologist to allow greater time allocated per patient, the intent being to prevent overbooking and allow buffer in the event that lengthier discussion time is needed with the provider.

Do:

Intervention Cohort 0

PDSA Cycle 1

Medical students used the Data Collection Form for at least 19 patient visits under supervision of Dr. Heath or Dr. Shields on Wed and Thurs clinic days. Arrival times at each station were recorded, then from those data we calculated the durations of stay in order to identify bottlenecks.

Intervention Cohort 1

-PDSA Cycle 2

We tested a change on 19 patients. Medical students again used the Data Collection form to acquire data that could be used to measure the efficacy of change. These data were analyzed descriptively to calculate the total transit time (TTT) through the clinic, and for comparison against the baseline TTT.

Study

Phase 1: April – May 2012

Question 1: What is the mean total time spent waiting? How can this be measured?

Prediction 1: Between 1-2 hours. Waiting times can be estimated as TTT minus the provider service time at individual clinic stations.

Question 2: What are subjective reactions of time tracker (patients/staff/medical student) to the visit?

Prediction 2: Long annoying waiting time for patient and staff is an acknowledged and perhaps even quietly accepted reality, but staff at isolated stations of each visit feel they are on track and not contributing to overall waiting. That is to say a comprehensive look at the clinic as a system is lacking.

Question 3: What is the bottleneck to the clinic system?

Prediction 3: Obtaining labs prior to scheduled appointment with oncologist. Not only is consultation with the oncologist often times dependent on patient lab results, but also any mishaps with the lab appointment could easily throw off subsequent scheduled events involving the oncologist.

Phase 2: June 2012 – April 2013

Question 4: How does the mean total time spent waiting change? Did we resolve bottlenecks without incurring extra cost or bottlenecks elsewhere?

Prediction 4: Mean TTT may not decrease by 20% with only one implemented change, but rather may require multiple incremental changes. Additional interventional phases would potentially maximize results and should ideally be studied if time permits within the study period.

Act:

Tested change to analyze root-causes.

Statistical endpoints: Let t_i denote the patient's arrival time at station i, for i = 1, 2, …., 11. Then $(t_{i+1} - t_i)$ measures the patient's duration of stay at station i, for all patients who visit stations 1 to 10 in sequence. The primary endpoint is TTT = $(t_{11} - t_1)$.

The secondary endpoints are 10 durations of stay at the successive stopping points or stations within the KCI Wertz Outpatient Clinic. The 10 secondary endpoints are denoted T_i, for i = 1, … , 10. Clearly, TTT = T_1 + …. + T_{10}, if all patients visit all stations, and do so in the anticipated sequence of station visits.

Statistical study design and sample size: This was a descriptive, single institution, pilot intervention study. It was not feasible to obtain pre- *and* post-intervention transit time data on the *same* set of patients, hence a paired data study design cannot be used in this pilot study. Thus, the baseline (pre-intervention) patients and the post-intervention patients will all be mutually exclusive (and statistically independent) groups.

Within each group of patients, it was desired to estimate the mean TTT to within 0.4 of a standard deviation (SD), with 90% confidence. This level of precision in the estimation of the mean TTT will require N=19 patients (as determined via PASS 2011 software, using the "Confidence Interval of a Mean" program). With N=19, the mean TTT could be estimated to within 0.398 SD's, with 90% confidence.

Statistical Analysis: Patients' arrival times at each of 11 different clinic "stations" were recorded. The duration of stay at each of the first 10 stations could then be calculated (under the "anticipated sequence" assumption), as well as the TTT. Summary statistics of the TTT of patients in each of Intervention Cohorts 0 (baseline) and 1 (first intervention) were computed. The primary statistical goal was to calculate the point and the 90% confidence interval (CI) estimate of the TTT for each patient cohort. We also performed sensitivity analyses of the impact on TTT estimation of excluding patients who did not visit Station 1, or patients who did not visit the clinic's infusion center.

RESULTS

The characteristics of the study patient population are presented in Table 1. The patients were predominantly male (32, or 89%), and most often Caucasian (16, or 48%). The 15 African-American patients accounted for 45% of the 33 patients with known race. The 2 most frequent primary diagnoses were prostate cancer and kidney cancer: 18 (53%) and 8 (24%), respectively. That was due to Dr. Heath's practice being focused on GU oncology. Of the 38 patients enrolled in the study, 34 were seen by Dr. Heath, and the other 3 were seen by Dr. Shields.

The estimated mean TTT values for Cohorts 0 and 1 were 139.5 and 131.1 minutes, respectively (Table 2). Hence, Cohort 1 experienced a slightly shorter TTT, by 8.4 minutes (i.e., by -6.0% [90% confidence interval -14.6% to +2.5%]). Given the small effective sample sizes (N=17 patients per cohort), the 90% CI's for the estimated mean TTT's are rather wide (25.6 and 32.8 minutes, respectively). The extensive overlap of the 90% CI's also suggests that the true mean TTT values for these two Cohorts might not be statistically different, but determining that was not a goal of this pilot study.

To better visualize the full TTT distributions, please see the multiple dotplots in Figure 2. Although the range of these 2 distributions is essentially the same, the dotplots allow one to infer their shapes. Cohort 0 has a more peaked distribution with most of its values concentrated between about 105 – 165 minutes. Cohort 1 has a flatter (i.e., more uniform) distribution with TTT values appearing throughout its full range of 77 – 195 minutes. Perhaps differences in the patient diagnoses between the two Cohorts (see Table 1) could be related to these differences in the TTT distributions.

Some additional statistics (e.g, 75th and 25th percentiles, and the interquartile range [IQR]) can be visualized from the multiple boxplots in Figure 4. The greater height of the "box" in the Cohort 1 distribution is a reflection of the larger standard deviation in that patient group (see Table 2).

Since two patients in each cohort of 19 did not visit Station 1 (the clinic lab), they could not be included in the primary analysis of TTT which is reported in Table 2 and Figures 2-3. A sensitivity analysis of that exclusion required analyzing the TTT of all patients who visited stations 2 (clinic registration) and 11 (exiting the clinic). This included 37 (not 34) patients, but would of course exclude any time spent at Station 1 (clinic lab). So, it might yield a downwardly biased mean TTT, but does allow us to include more patients. That analysis yielded estimated mean TTT values for Cohort 0 (n= 18) and Cohort 1 (n=19) of 118.8 and 119.5 minutes, respectively. Those estimated means are so close as to suggest that patient time spent in the clinic lab (Station 1) might deserve further investigation in the future.

Two other patients (both in Cohort 0) ended up going to the clinic's infusion center, even though that should have rendered them study ineligible. That might have yielded an upwardly biased estimate of mean TTT of the Cohort 0 patients. After excluding those 2 patients we performed a second sensitivity analysis of TTT among the remaining 15 Cohort 0 and the 17 Cohort 1 patients. That analysis yielded estimated mean TTT values for Cohorts 0 and 1 of 140.7 and 131.1 minutes, respectively. Of course the Cohort 1 estimate would be the same as the original estimate. However, the Cohort 0 estimate is nearly identical to its original estimate of 139.5 minutes. Hence, it appears that time spent in the infusion center had little impact on Cohort 0 patients' TTT, and/or they did not undergo any infusion at all despite visiting that clinic station.

Contrary to the study plan, there were rather frequent "out of sequence" patient arrivals at the 11 different clinic stations. In other words, $(t_{i+1} - t_i)$ did not always correctly measure a patient's duration of stay at station i. This precluded any direct analysis of duration of stay at each of stations 1-10 until an

extensive restructuring of the arrival times chronologically is performed, irrespective of station sequence. Those inter-station results will be reported separately.

DISCUSSION

At baseline, patients' mean TTT was 139.5 minutes. After intervention 1, (a different set of 19) patients' mean TTT was 131.1 minutes, a reduction of 8.4 minutes or 6.0%. Although any reduction in TTT is relevant, a mean reduction of 6% may not be of large benefit per an individual patient, especially given the 90% confidence interval was rather wide. However, such a reduction may be worthwhile per clinic, that is, from a clinic operations improvement standpoint. The implementation of intervention 1 was relatively simple: add 5 minutes to normal appointment times allocated for seeing the oncologist to prevent overbooking and to allow for longer discussion. A second intervention was planned but not executed in time during the study period. It required interdisciplinary work, as medical students communicated with clinic nurses to solicit ideas, then coordinated with the pharmacist overseeing the clinic's automated medication management system.

There were several limitations to this pilot study. First, the study design should have been 1-sample (not 2 sample), with repeated measures on the exact same set of patients, i.e., a pre/post design in which each patient served as their own control. That was completely impractical; hence the 2-sample design had to be used. This admits the potential for confounding of patient-specific factors with any intervention attempted, which hampers a clear interpretation of the intervention effect, per se. Second, the anticipated sequence of patient arrivals at the successive clinic stations 1-11 was often not observed. Those station sequence deviations precluded any direct analysis of duration of stay at each of stations 1-10 for the purpose of this report. Third, we placed great reliance on a cadre of 16 medical students to volunteer their time to track patients on their journey through the clinic. This required intensive time spent recruiting, training, and retaining students by aligning student goals with project goals (e.g. shadowing hours, research involvement). This data collection method allows for variation in the data due to having multiple observers. Since each patient was tracked by only one medical student, we have no way of estimating intra-observer variability. It became clear that in the future, we would need to shorten our data collection form based on a simple yet useful model already used by Kallen et al (16).

To improve a study like this, we would only capture the patient's appointment time with their oncologist and the time the oncologist sees the patient. Those data would allow us to determine wait times (*per se*) at that one specific clinic station, in lieu of recording patient's arrival times at every clinic station of the patient's visit as previously attempted with great difficulty. Then we would use PDSA cycles to monitor changes in mean wait times. As we tested each change, we would implement the ones that succeed, allowing for multiple successful changes to take effect at incremental cycles.

Alternatively we could use a simulation process to determine the most effective solutions without introducing the variability of having multiple trackers nor undercutting the feasibility of completing a study with a statistically adequate sample size. Increasingly many authors are using discrete-event computerized simulation as a useful analysis and improvement tool in industry settings that involve high levels of complexity and uncertainty, including health care (17, 18). Hence simulation process could be a future direction for this research, as we have already provided process mapping for root cause analysis (i.e. our baseline cohort) from which simulation modeling could then explore potential effective solutions.

Additional ideas considered for intervention included implementing a system with the preexisting flags that were installed over patient exam room doors, which no longer are prevalently used to facilitate inter-professional communication among current staff. Also patient arrival white boards once existed to note when patients were ready to be seen by their oncologist, but similarly are no longer utilized now. Use of electronic medical records was considered to track times of patient check in to labs, sign in to clinic, retrieval of vitals, and arrival of oncologist in the exam room, but this was too much of an infrastructural and technological challenge to attempt in the span of this study. Use of a smart phone application for patients to track their own times also was suggested in lieu of students physically accompanying the patients, but that was a challenge that would have added to clinic costs.

Acknowledgements

Each medical student participating in this study tracked one or more patients in the Karmanos Cancer Institute Wertz Outpatient Clinic, and recorded the patient's arrival times at the various stations within the clinic. The project author tracked 5 patients.

These 15 other participating medical students were: David Broome (tracked 6 patients); Natalja Stanski (5); Andy Parajpe (4); Nabil Al-Kourainy (3); Erin Ryan (3); Jason Yaldo (3); Elizabeth Perry (2); Ashley Anderson (1); Donghan Sohn (2); Megan Franzo-Roman (1); Ashley Matusz (1); Hammad Ali (1); and Brandon Twardy (1).

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Conflicts of interest

Kimberly Ku as a medical student at Wayne State University School of Medicine was awarded the Blue Cross Blue Shield of Michigan Foundation Student Award Program 2011-198 grant of $3,000.00 for her project "Improving Patient Flow in the Outpatient Cancer Clinic," for the academic years 2011-2013. She has no other potential financial and personal conflicts of interest.

Dr. Elisabeth Heath is the project preceptor who oversaw all endeavors. She is an oncologist at the Karmanos Cancer Institute, Director of Prostate Cancer Research, and Full Professor of the Department of Oncology for Wayne State University School of Medicine. She has no financial or personal conflicts of interest with this project.

Dr. Heilbrun is the project Biostatistician for study design, and statistical analysis planning. He is the Assistant Director of the Biostatistics Core of the Karmanos Cancer Institute. He has no financial or personal conflicts of interest with this project. Daryn Smith is a Biostatistician in the Biostatistics Core of the Karmanos Cancer Institute. He provided the data processing and statistical computing and statistical graphics support for this project. He has no financial or personal conflicts of interest with this project.

Table 1. Patient Characteristics (N = 38)

Patient Characteristic	Cohort		
	Baseline	Intervention	Total
	(n = 19)	(n = 19)	(n = 38)
	n (%)	n (%)	n (%)
Age: median (range)	69 (51 – 84)	64 (41 – 90)	67 (41 – 90)
Sex: male	17 (89%)	15 (88%)	32 (89%)
female	2 (11%)	2 (12%)	4 (11%)
Race: Caucasian	8 (42%)	8 (57%)	16 (48%)
African-American	10 (53%)	5 (36%)	15 (45%)
Other	1 (5%)	1 (7%)	2 (6%)
Cancer site diagnosis:			
Prostate	9 (60%)	9 (47%)	18 (53%)
Kidney	4 (27%)	4 (21%)	8 (24%)
Bladder	1 (7%)	0 (0%)	1 (3%)
Other GU	0 (0%)	3 (16%)	3 (9%)
Pancreas	1 (7%)	0 (0%)	1 (3%)
Other GI	0 (0%)	1 (5%)	1 (3%)
Lung or bronchus	0 (0%)	2 (11%)	2 (6%)
Physician:			
E. Heath	18 (95%)	17 (89%)	35 (89%)
A. Shields	1 (5%)	2 (11%)	3 (11%)

Sample sizes may not sum to 19 in each cohort due to occasional missing data.

Percentages are computed from the number of patients without missing data.

Table 2. Summary statistics of total transit time (TTT) by cohort (N = 34)

TTT statistic	Cohort	
	Baseline (Cohort 0)	Intervention (Cohort 1)
N	17	17
Mean (in minutes)	139.5	131.1
Upper 90% CL for mean	152.3	147.5
Lower 90% CL for mean	126.7	114.7
Standard deviation	30.2	38.7
Maximum	195.0	195.0
Median	146.0	137.0
Minimum	81.0	77.0

CL = confidence limit

Figure 1. Data collection Form for Study Period 2012-2013

KCI Outpatient Clinic Flow (OCF) Study: Data Collection Form

Patient Study ID # _____ **Intervention cohort #** ____ (0, 1, or 2)

Age: ____ **Gender:** _____ **Race:** _____

Diagnosis: _____

Patient Visit Date: _____ **Assigned Physician:** _____

Medical student tracker: _____

Wertz Outpatient Clinic Patient Arrival Times at each Station

For each station, record the patient's arrival time (e.g., "8:30 am" or "2:30 pm", and circle either "am" or "pm"). If the patient does not visit a given station, mark an "x" in the hour box instead of time.

Actual Arrival Time	Scheduled Appointment Time
1. _ _ : _ _ am/pm Time patient signed in to Lab	1. _ _ : _ _ am/pm Lab appointment time
2. _ _ : _ _ am/pm Time patient registered with Wertz Outpatient Clinic	
3. _ _ : _ _ am/pm Time patient was called to enter clinic	
4. _ _ : _ _ am/pm Time patient's vital signs were obtained	
5. _ _ : _ _ am/pm Time patient arrived in exam room	
6. _ _ : _ _ am/pm Time nurse came into room for routine questions	
7. _ _ : _ _ am/pm Time provider #1 came into exam room	2. _ _ : _ _ am/pm Doctor appointment time
8. _ _ : _ _ am/pm Time provider #2 came into exam room	
9. _ _ : _ _ am/pm Time provider #3 came into exam room	
10. _ _ : _ _ am/pm Time patient started to schedule their next appointment	
11. _ _ : _ _ am/pm Time patient left the hospital	

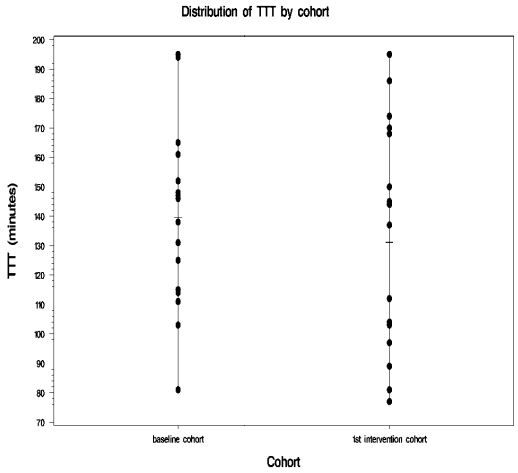

Figure 2 Dotplot distributions of total transit time (TTT) for patients in the baseline Cohort 0 (N=17) and in the intervention Cohort 1 (N=17)

Note: horizontal line on each dotplot marks the mean value.
Note: two patients in each cohort of 19 did not visit Station 1 (the clinic lab), hence the effective sample sizes for calculating TTT were 17 patients per cohort.

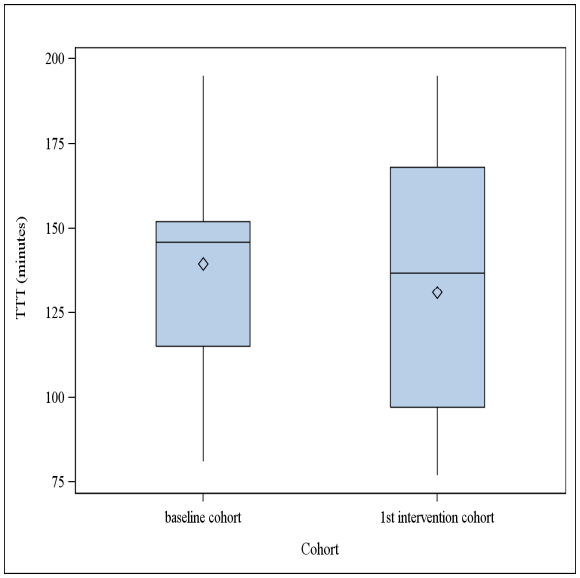

Figure 3 Boxplot statistics of total transit time (TTT) for patients in the baseline Cohort 0 (N=17) and in the intervention Cohort 1 (N=17)

Note: two patients in each cohort of 19 did not visit Station 1 (the clinic lab), hence the effective sample sizes for calculating TTT 17 patients per cohort.

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