Mixed methods approach for understanding clinical workflow

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DEDICATION

To my husband and children without whom this thesis would have been completed years earlier.

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1. Introduction

The transition to fully integrated electronic patient records has resulted in vast amounts of information being collected and archived[1]. These data accumulate in clinical repositories with much higher velocity and have much more variety and variability than ever before [2][3][4][5], which creates significant opportunities for new analyses and medical research [6][7]. Although this wealth of Big Data is extremely promising, the temptation to make causal inferences through purely computational methods based on the data alone can lead to potentially dangerous false conclusions about causality based only on correlation[8], [9]. Experts have repeatedly called for deeper exploration of causal factors underlying data analytics conclusions[10][11][12][13] through initiatives such as Big Mechanism [14], but no clear path towards achieving this goal has been identified [15].

One potential way to address the causality challenge in dealing with Big Data is by pairing data analytics with other approaches, such as qualitative methods. Qualitative methods can assist with understanding clinical processes through the perspectives of the participants [16][17]. Qualitative approaches can explore how people use technology [18], can help with understanding existing workflow patterns [19], and can provide explanations for bottlenecks.

Qualitative studies generate a wealth of information about human behavior in relation to the processes healthcare workers complete and technologies that are available to them [20]. Despite the positive contributions qualitative methods can make, qualitative methods face challenges of scale across space, time and human participants.

Our research focuses on the study of clinical workflow at a large comprehensive cancer center. Currently in the United States, cancer is the second leading cause of death after heart disease [21]. Moreover, the Center for Disease Control (CDC) estimates that chronic and mental conditions account for eighty-six percent of the nation's $2.7 trillion annual health care expenditures [22], costs which can be reduced [23]. Cancer care alone amounted to $157 billion in 2010 dollars[23], 58% of which is allocated to hospital outpatient or office based provider visits [24].

Traditionally, medical workflow has been studied either through qualitative methods[25][26][27] or by looking at metrics considered to be proxies of workflow processes[28]. Given the complex nature of the medical field[29], where context is critical, we propose a mixed-methods approach that links qualitative methods with data analytics to model clinical workflow and make causal inferences. The result is a systematic analysis of the clinical workflow processes based on an understanding of clinical environment: the skills and perceptions of the staff, the technologies in use, the clinical processes being followed, the geography of the space, the temporal evolution of the environment, etc.

The rest of this manuscript is organized as follows: Chapter 2 is a background section that puts our work in the context of others. Chapter 3 gives a description of the quantitative and qualitative methods. Chapter 4 presents workflow findings that illustrate the value of the methodology. Chapter 5 is a discussion of the results and the methodology. Chapter 6 contains concluding remarks and future directions.

2. Background

The study of workflow originates in the manufacturing setting. In the early 1900, researchers such as Taylor[30] and Gilbreth[31] started exploring ways to improve the efficiency of industrial processes. The clinical environment is significantly more dynamic that the manufacturing setting, so historically the study of medical workflow has been multidisciplinary borrowing from psychology, sociology and engineering[32].

Our methodology uses qualitative studies to explain the complexities of human interaction in clinical settings which analytics alone cannot describe [33], and quantitative studies in an attempt to scale the analysis across time, space and human participants. This type of approach has been applied to other types of projects [34][35][36][37][38][37]. However, a number of researchers [34][39] mention the difficulty of combining the two approaches due to the fact that they have very different assumptions. As discussed in [40], one way to reconcile the two paradigms is to assign a priority to either the qualitative or the quantitative investigation. Through our approach we demonstrate that the qualitative and quantitative can contribute equally to a comprehensive understanding of the results. We are able to use this approach because our research question is very well defined and focused on clinical workflow. The second way to reconcile the paradigms consists of deciding on how whether the qualitative and the quantitative are going to be executed simultaneous or sequentially and if so, the order [37][40]. We used a sequential approach starting with a qualitative phase.

The qualitative methods consisted of mainly ethnographic observations of workflow[41] [42]. This method is well established and offers a series of benefits [43][44]. In addition to adding context, it also helps the researcher become more open minded and able to describe the environment through the perspectives of the participant. It allows the researcher to see things that people in the setting might miss and also learn things that people are unwilling to talk about in interviews. We also extracted qualitative data from conversations with staff and leadership but we verified them during workflow observations.

Our analytical methods use primarily time series analyses and visualizations of clinical data. They also include statistical methods such as a t-test [45] and Pearson correlation coefficient calculation [46].

3. Methods

3.1 Overview

Our methods integrate data analytics with qualitative observations of people, processes and use of technologies. This approach allows for assertions from data based on an understanding of the environment. Figure 1 shows an overview.

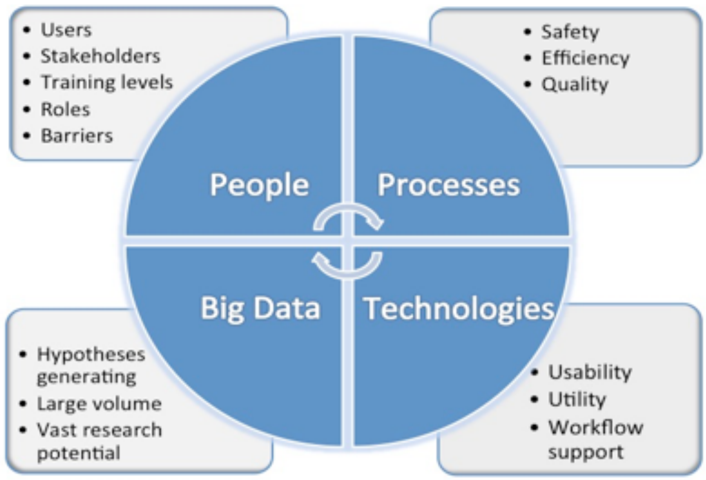


Figure 1. Evaluation model

3.2 Environment

The Vanderbilt Ingram Cancer Center (VICC) is one of 41 National Cancer Institute (NCI)-designated Comprehensive Cancer Centers. The clinic manages the care of over 17,000 patients yearly with over 230 patients seen daily. The VICC patient care areas are geographically distributed on 2 floors and different sections of the Vanderbilt Clinic and consist of a registration area, a laboratory, a medical clinic, an infusion center, a chemo pharmacy and a stem cell and transplant area. The inherent complexity of outpatient oncology care delivery, made VICC an ideal setting to explore the potential of our mixed methods approach to clinical workflow evaluation.

3.3 Qualitative methods

Vanderbilt's Institutional Review Board approved all study procedures. Before each observation, the project was explained to staff members as well as to individual patients and verbal assent was obtained. The researcher also distributed the Institutional Review Board Informed Consent Document for Research to all the staff members observed. Prior to the initiation of this study the student had completed coursework on observation techniques, had been involved in another observation study at a cancer infusion center and had studied the literature on chemotherapy management.

Over the course of two months during the summer of 2014, one researcher (ID), a graduate student in biomedical informatics observed healthcare team members for 31 hours at the infusion center, the infusion center front desk, the VICC registration desk, the laboratory front desk, the laboratory, the pharmacy, and the cancer clinic exam rooms. During this process, we observed 3 infusion center nurses, 1 infusion center patient care tech, 3 front desk patient services representatives (PSR), 2 lab nurses, 2 pharmacists, 3 medical doctors (2 oncology attendings, and 1 oncology fellow), and 2 certified medical assistants (CMAs). During this round, our observations focused on the clinical workflow and the use of electronic systems with an emphasis on the Outpatient Whiteboard. We present the workflow diagram based on these observations in the results section.

Over the course of two weeks during the spring of 2017, one researcher (ID) performed 8 additional hours of observations at the VICC registration desk, the laboratory front desk and the laboratory. We observed: 2 front desk PSRs and 2 licensed practical nurses and focused on the clinical workflow changes since 2014, new communication patterns and the use of the following electronic systems: Outpatient Whiteboard, Starpanel (notes, orders), Cerner Lab System and Epic Appointment Scheduler.

After the implementation of a new EHR one researcher (ID) performed 3 hours of observations at the VICC registration desk, the laboratory front desk, the laboratory, the clinic intake area, and in the clinic team room. These observations focused on the impact of the new EHR on workflow.

In addition to observations, we also gathered qualitative data during 3 one hour meetings with the VICC leadership.

We validated our observations using a few well-established methods in the field. Triangulation [47] is a method where the researcher uses multiple sources to corroborate the information. Since the processes at the VICC are extremely interconnected and involve stringent communication between staff members, it was easy to verify the information by checking with multiple sides since they multiple people were aware of the workflow at other areas. Member checking[48] in which the study findings are presented to team members for verification is another technique we used to validate our findings. In addition to the clinical staff in the field, we also verified our findings through meetings with the VICC leadership. Both the staff members and leadership also contributed to the validation of our findings through collaboration[49] a technique in which the research subjects participated to the formulation of the research questions. The other validation methods used were prolonged exposure in the field [50] in which the researcher visited the research areas repeatedly (summer 2014, spring 2017 and winter 2017) and peer debriefing [48] with the researcher's mentor and the primary investigator (KMU) and two members of the faculty of the Department of Biomedical Informatics (STW and DF).

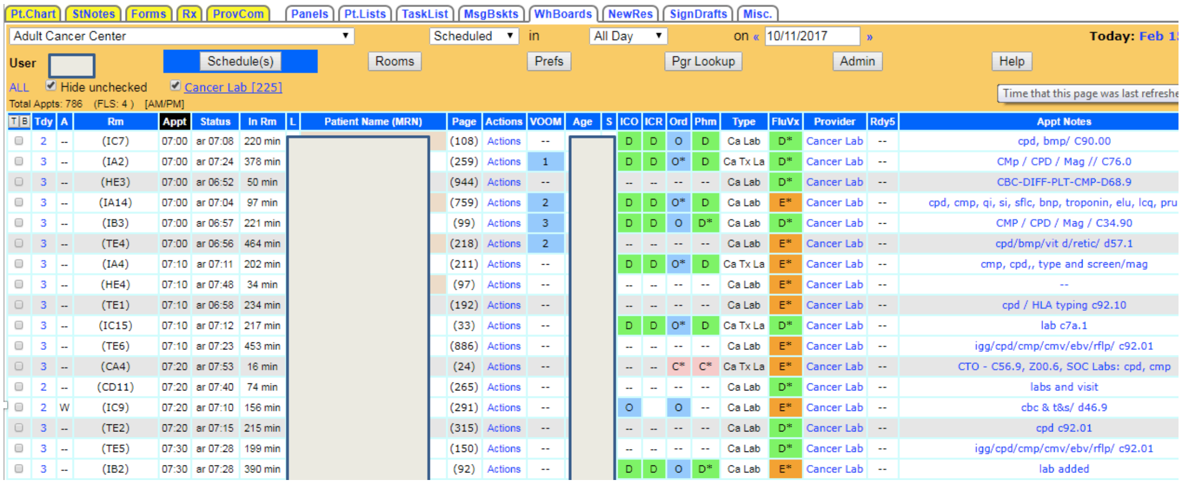
3.4 Data analysis

We obtained an additional IRB approval for the data analysis which covered access to the data sources and required the medical record number (mrn) be de-identified.

We prototyped and tested our framework using data generated primarily from the Outpatient Whiteboard [51][52] intended to manage patient room movement and to facilitate communication between the healthcare team and patients. In the last year on average 1900 Whiteboard transactions have been recorded on 225 patients daily Monday-Friday at VICC.

The outpatient interactions with the healthcare system often consist of a series of consecutive events, and not a continuum of care like the inpatient settings. The Outpatient Whiteboard provides the glue for these discrete events at the Vanderbilt University Medical Center (VUMC) Outpatient Clinics. It aggregates various data such as appointments, laboratory results, pharmacy medication dispenses etc, into a user-friendly web interface that allows users to monitor and communicate about their patients.

While different outpatient clinics at VUMC have integrated the Outpatient Whiteboard to varying degrees into their daily operations, the Vanderbilt Ingram Cancer Center (VICC) uses the Whiteboard as their main workflow and communication tool. Some of the information captured in the Whiteboard is automatically generated, while administrative staff, nurses, physicians, and others manually enter other data. Figure 2 shows a screenshot of the VICC lab area view.



T B	Tdy	A	Rm	Appt	Status	In Rm	L	Patient Name (MRN)	Page	Actions	VOOM	Age	S	ICO	ICR	Ord	Phm	Type	FluVx	Provider	Rdy5	Appt Notes
	2	--	(IC7)	07:00	ar 07:08	220 min			(108)	Actions	--			D	D	O	D	Ca Lab	D*	Cancer Lab	--	cpd, bmp/ C90.00
	3	--	(IA2)	07:00	ar 07:24	378 min			(259)	Actions	1			D	D	O*	D	Ca Tx La	D*	Cancer Lab	--	CMp / CPD / Mag // C76.0
	3	--	(HE3)	07:00	ar 06:52	50 min			(944)	Actions	--			--	--	--	--	Ca Lab	D*	Cancer Lab	--	CBC-DIFF-PLT-CMP-D68.9
	3	--	(IA14)	07:00	ar 07:04	97 min			(759)	Actions	2			D	D	O*	D	Ca Lab	E*	Cancer Lab	--	cpd, cmp, qi, si, sflc, bnp, troponin, elu, lcq, pru
	3	--	(IB3)	07:00	ar 06:57	221 min			(99)	Actions	3			D	D	O	D*	Ca Lab	D*	Cancer Lab	--	CMP / CPD / Mag / C34.90
	3	--	(TE4)	07:00	ar 06:56	464 min			(218)	Actions	2			--	--	--	--	Ca Lab	E*	Cancer Lab	--	cpd/bmp/vit d/retic/ d57.1
	3	--	(IA4)	07:10	ar 07:11	202 min			(211)	Actions	--			D	D	O*	D	Ca Tx La	E*	Cancer Lab	--	cmp, cpd,, type and screen/mag
	3	--	(HE4)	07:10	ar 07:48	34 min			(97)	Actions	--			--	--	--	--	Ca Lab	E*	Cancer Lab	--	--
	3	--	(TE1)	07:10	ar 06:58	234 min			(192)	Actions	--			--	--	--	--	Ca Lab	E*	Cancer Lab	--	cpd / HLA typing c92.10
	3	--	(IC15)	07:10	ar 07:12	217 min			(33)	Actions	--			D	D	O*	D	Ca Tx La	D*	Cancer Lab	--	lab c7a.1
	3	--	(TE6)	07:10	ar 07:23	453 min			(886)	Actions	--			--	--	--	--	Ca Lab	E*	Cancer Lab	--	igg/cpd/cmp/cmv/ebv/rflp/ c92.01
	3	--	(CA4)	07:20	ar 07:53	16 min			(24)	Actions	--			--	--	C*	C*	Ca Tx La	E*	Cancer Lab	--	CTO - C56.9, Z00.6, SOC Labs: cpd, cmp
	2	--	(CD11)	07:20	ar 07:40	74 min			(265)	Actions	--			--	--	--	--	Ca Lab	D*	Cancer Lab	--	labs and visit
	2	W	(IC9)	07:20	ar 07:10	156 min			(291)	Actions	--			O		O	--	Ca Lab	E*	Cancer Lab	--	cbc & t&s/ d46.9
	3	--	(TE2)	07:20	ar 07:15	215 min			(315)	Actions	--			--	--	--	--	Ca Lab	D*	Cancer Lab	--	cpd c92.01
	3	--	(TE5)	07:30	ar 07:28	199 min			(150)	Actions	--			--	--	--	--	Ca Lab	D*	Cancer Lab	--	igg/cpd/cmp/cmv/ebv/rflp/ c92.01
	3	--	(IB2)	07:30	ar 07:28	390 min			(92)	Actions	--			D	D	O	D*	Ca Lab	E*	Cancer Lab	--	lab added

Figure 2. Outpatient Whiteboard view of the lab work area

The OPWB data was an integral part of our quantitative data analysis because it stored the transactional activities in a very consistent manner, as shown in Figure 3: appointment date, medical record number, action timestamp, status (in/out of the room, patient paged, pager returned etc.), higher level location information (Adult Cancer Center), user id and name of the staff member performing the operation, name of the room. For our analyses, we used all of these parameters, which allowed for a straightforward analysis of workflow.

APPOINTMENT_DATE	MRN	ACTION_DATETIME	ACTION_CODE	DISPLAY_TEXT	ADDL_TEXT	RACFID	ROOM
01-JAN-19	123456789	01-JAN-19 08:00	A	a166 - assigned	(null)	smith	(null)
01-JAN-19	123456789	01-JAN-19 08:00	P	p166 - "Please meet Ruby at desk R10	(null)	madonna	(null)
01-JAN-19	123456789	01-JAN-19 08:00	I	Put in: LabWR	Adult Cancer Center	madonna	LabWR
01-JAN-19	123456789	01-JAN-19 08:00	O	Out of: LabWR	Adult Cancer Center	prince	LabWR
01-JAN-19	123456789	01-JAN-19 08:00	I	Put in: Lab7	Adult Cancer Center	prince	Lab7
01-JAN-19	123456789	01-JAN-19 08:00	O	Out of: Lab7	Adult Cancer Center	gaga	Lab7
01-JAN-19	123456789	01-JAN-19 08:00	I	Put in: DocWR	Adult Cancer Center	gaga	DocWR
01-JAN-19	123456789	01-JAN-19 08:00	P	p166 - "We are ready to bring you back...	(null)	sting	(null)
01-JAN-19	123456789	01-JAN-19 08:00	O	Out of: DocWR	Adult Cancer Center	sting	DocWR
01-JAN-19	123456789	01-JAN-19 08:00	I	Put in: CA5	Adult Cancer Center	sting	CA5
01-JAN-19	123456789	01-JAN-19 08:00	O	Out of: CA5	Adult Cancer Center	gaga	CA5

Figure 3. Outpatient Whiteboard data in the Enterprise Data Warehouse

We used the room movement data, patient location being an important component of workflow analysis that we not could accurately obtain using EHR access logs.

In addition to room movement, the Whiteboard is also used as a non-verbal communication in three ways. Firstly, by providing different types of status flags such as: orders done, is patient wheelchair, have the labs been completed, has the patient had a flu vaccine etc., it allows users to see all the workflow information easily on one screen. Secondly, it offers the capability to connect with the patient paging system, such that clinical staff can communicate in real time with their patients. Thirdly, for the VICC, it provides communication between nurses and pharmacists at the infusion center for an efficient delivery of chemotherapy medication. For our analyses, we used data from the patient paging branch to estimate time delay between when they have been paged to when they present to the respective desk.

As part of our analysis we extracted our data from the Enterprise Data Warehouse (EDW), protocol approved by the Vanderbilt Medical Center Institution Review Board. We stored the analyses onto a secure server located inside the VUMC perimeter firewall.

The inclusion criteria for the study population consisted of the Outpatient Whiteboard room movement data recorded on days and for patients who visited the VICC over the course of 3 years: 1/1/2014-11/1/2017. For each (patient, VICC visit date) tuple we selected all Whiteboard location transactions, which include outpatient visits to clinics and areas outside of VICC. Using an Oracle hash function, we transformed medical record numbers into unique subject identifiers using a low collision, one way, algorithm. We excluded transitions that did not result in patients being discharged from the Whiteboard at clinic closing. As part of the analysis phase we also grouped the individual rooms into 7 location sets based on qualitative observations as shown in Table 1.

Location group	Description	Location
LabWR	Lab waiting area	Vanderbilt clinic 1st floor
Lab	Lab area	Vanderbilt clinic 1st floor
DocWR	Clinic waiting area	Vanderbilt clinic 1st floor
Doc	Clinic	Vanderbilt clinic 1st floor
EnRte	In route to other area	
InfWR	In route to infusion	
Chemo	Infusion waiting area	Vanderbilt clinic 2nd floor
Inf	Infusion	Vanderbilt clinic 2nd floor

Table 1. Location description

Because multiple Whiteboard users will sometimes move patients into the same room, we chose the earliest date and time as a proxy for the room movement initiation.

We compared the timing of the Whiteboard room movement with appointment date time, and the patient clinic check-in date and time. We also compared the Epic appointment scheduling data and with Whiteboard paging information to see if patients were seen even if they were early for their appointments.

In addition to using it for workflow analysis, another question raised was whether the Whiteboard patient movement activities were redundant given the access logs to the EHR are available as a data source. Based on the qualitative observations we created a side-by-side comparison of the information contribution by each of the two methods. These data are also available in the results chapter.

Other data sources included: Epic appointment scheduling system (checkin date, appointment time), Starpanel access log data for the PortAccessFlowsheet document (webpage accessed, access time, access racfid, access ip address), data regarding job titles and work schedules from Kronos the human resources system (employee id, shift start date, shift end date, location) and job roles and department information from the human resources database (employee id, job title, department). We used a commercial analytics package called Tableau™ to visualize all the analyses. This data visualization package has easy drag and drop capabilities and easy integration with a variety of databases. In addition, it has a large online community that helps troubleshoot issues that come up. The trends observed are available in the results section.

3.5 Mixed methods

Our approach consists of iterative rounds of quantitative and qualitative data collected in sequential phases. The result of the first round of qualitative observations is a high-level workflow diagram. It captures an overview of the patient flow through the clinical areas, the job titles of the staff, and their specific duties. In the next phase, a round of quantitative analyses identifies workflow trends based on data generated by the electronic systems. Our methodology then consists of iterative rounds of qualitative and quantitative data analyses each meant to answer some of the questions raised during the previous phase and perhaps pose new questions. Figure 2 shows an overview.

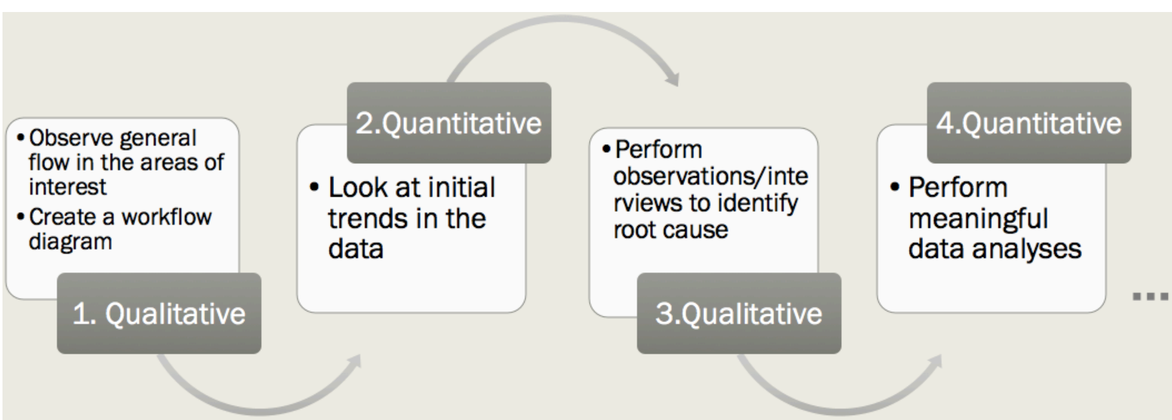


Figure 4. Methodology overview

4. Results

The first step in our approach is a qualitative survey of the clinical environment that results in a high-level workflow diagram shown in Figure 3. The patient flow through the clinic has multiple alternatives, indicative of the complex processes performed at the VICC. There are three entry points into the system: the VICC front desk registration, the hematology/transplant area and the waiting area at the infusion center. There are multiple exit points from the system: hematology/transplant, lab, exam room, procedure room, chemo and infusion. The job titles vary greatly and show staff with a diverse range of skills and job duties.

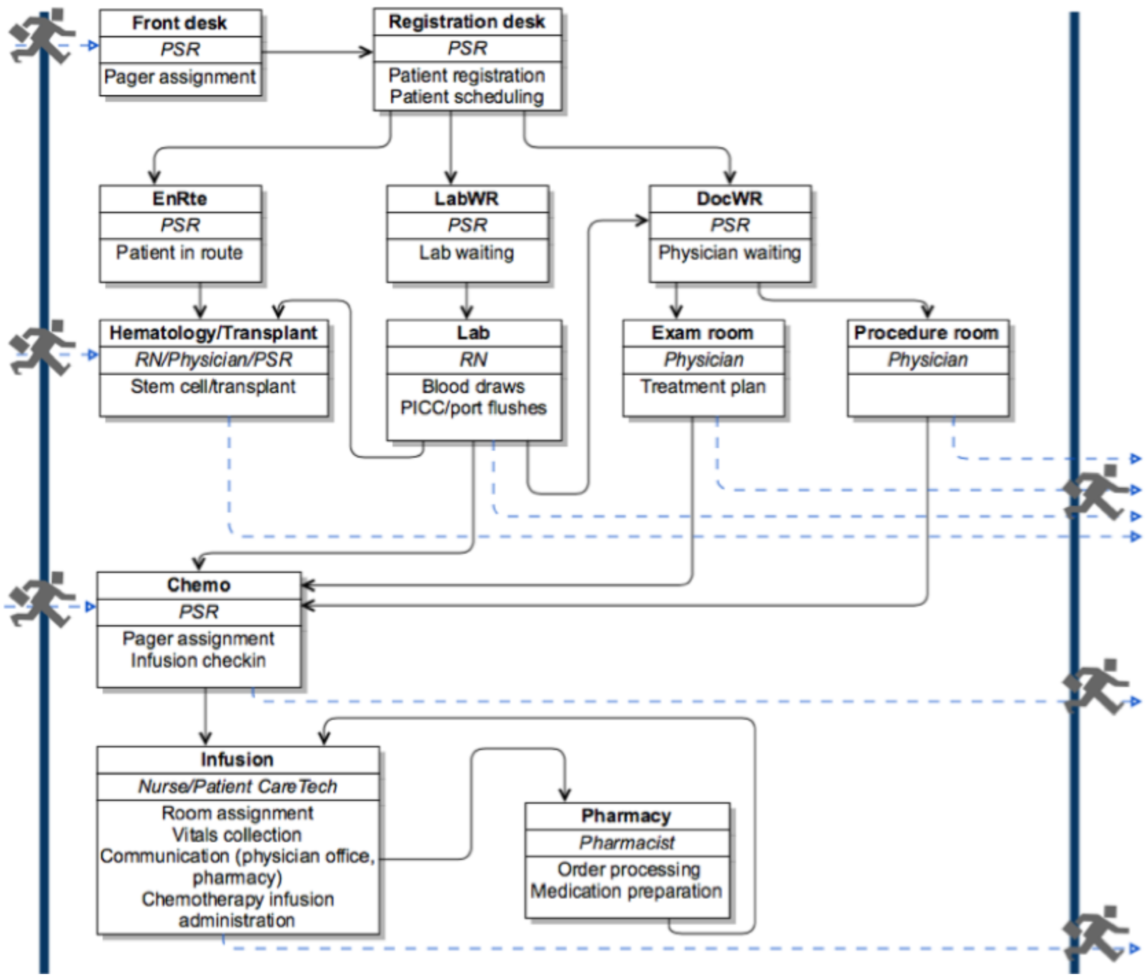


Figure 5. VICC workflow diagram

The initial qualitative analysis was followed by a quantitative one where we analyzed workflow trends captured by the Whiteboard room movement data. During this analysis, the most significant was a decrease in the wait times at the lab from 17 minutes on average in 2014 to 7 minutes in 2017. There is also a decrease in wait times at the oncology clinic from around 18 minutes to 13 minutes. At the same time, during 2014 and 2017 the patient population served by the cancer center increases from 289 patients seen per day to 317. These trends are illustrated in Figure 4 that aggregates data on a weekly level.

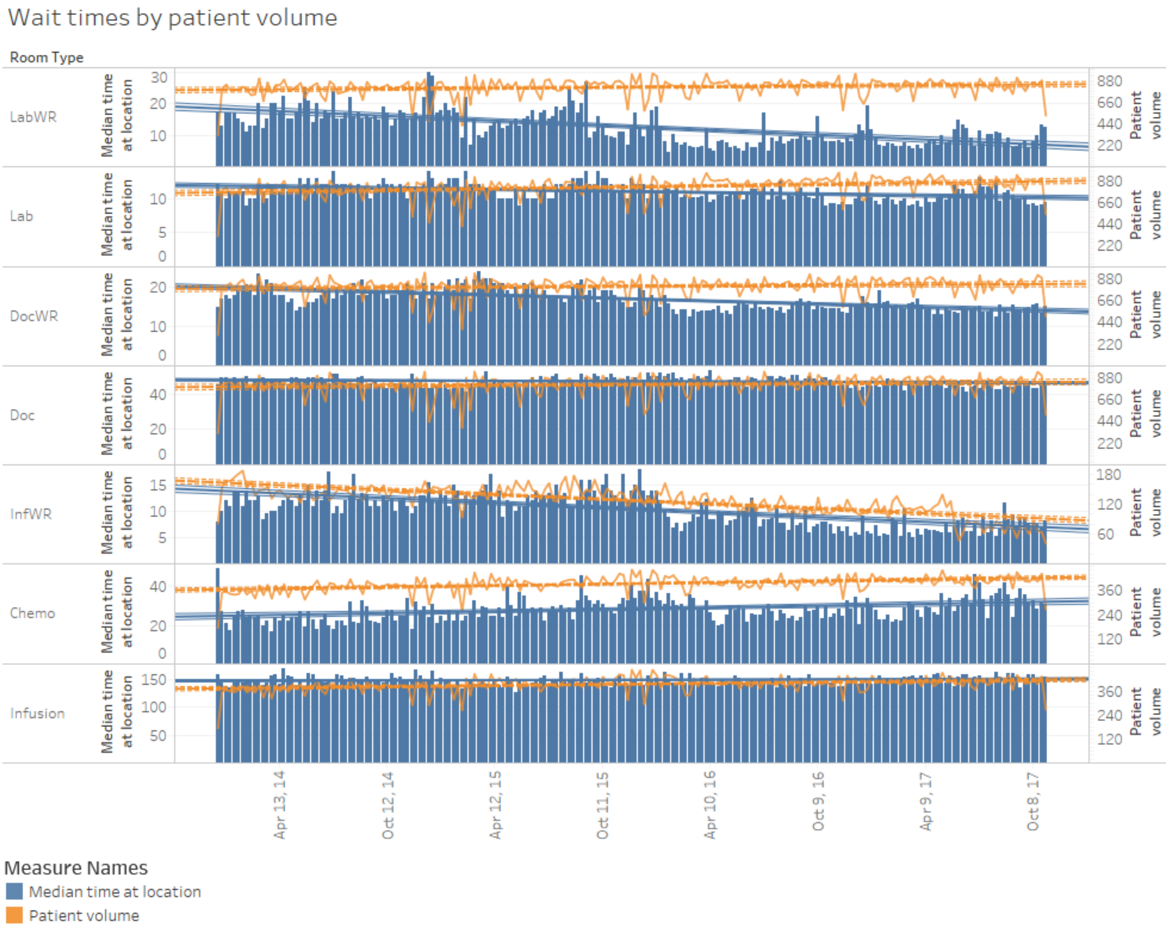


Figure 6. VICC median wait time trends (blue bars) versus patient volume (orange line)

The decreased wait time at the lab is an interesting workflow finding, so in the next steps we illustrate the use of our methodology using sequential rounds of qualitative and quantitative analyses. The full list of questions and explanations that we investigated to illustrate our methodology is shown in Table 2 below. The remainder of the results section covers each of these issues.

Phase	Issue to understand	Results	Information sources
1. Qualitative		Create a workflow diagram of the cancer center (task performed, performer, flow)	Workflow observations
2. Quantitative		Reduction in wait times at the lab and doctor's office	whiteboard patient movement
3.a. Qualitative	Reduction in wait times at the lab and doctor's office	Increased staffing in the lab	Conversations with leadership
3.b. Qualitative	Reduction in wait times at the lab and doctor's office	Less paperwork for the front desk registration staff	Conversations with leadership
3.c. Qualitative	Reduction in wait times at the lab and doctor's office	PSR at lab trying to get patients in faster even if early for their appointments	Conversations with staff
3.d. Qualitative	Reduction in wait times at the lab and doctor's office	Better utilization of chair 8	Conversations with staff
3.e. Qualitative		Chair 8 still problematic due to proximity to door and staff area behind it	Direct observation
3.f. Qualitative		Pager problems (pages not received)	Direct observation
3.g. Qualitative		Patients with ports take longer due to need for documenting port access information	Direct observation

4.a. Quantitative	Increased staffing in the lab	Number of staff members and hours worked has increased	kronos, hr database
4.b. Quantitative	Less paperwork for the front desk registration staff	not electronic documentation.	
4.c. Quantitative	PSR at lab trying to get patients in faster even if early for their appointments	decrease in time it takes for the patient to be assigned to a lab seat	whiteboard patient movement
4.d. Quantitative	Better utilization of chair 8	chair 8 is utilized as much as the others.	whiteboard patient movement , epic appointment scheduling system
4.e. Quantitative	Chair 8 still problematic due to proximity to door and staff area behind it.	chair 8 is utilized as much as the others.	whiteboard patient movement, whiteboard paging information
4.f. Quantitative	Pager problems (pages not received)	decrease in number of patients paged; for the patients that are paged: increase in time it takes to respond to pages	whiteboard patient movement
4.g. Quantitative	Patients with ports take longer due to need for documenting port access information	ports seem to take on average 10% more time	whiteboard patient movement, starpanel access logs

Table 2. Workflow questions answered qualitatively and quantitatively

Through conversations with leadership, the factors responsible for the decrease in wait times were: increased staffing at the lab and less paperwork for the front desk registration staff (Issues 3.a. and 3.b. in Table 2). Using the human resources hourly employee timesheet data (kronos), we performed an analysis of the staffing at the lab by the number and employees and also the total number of hours worked (4.a. in Table 2). Figure 5 shows these data. Overall both the number of employees at the lab as well as the total number of hours worked has increased by about 50%.

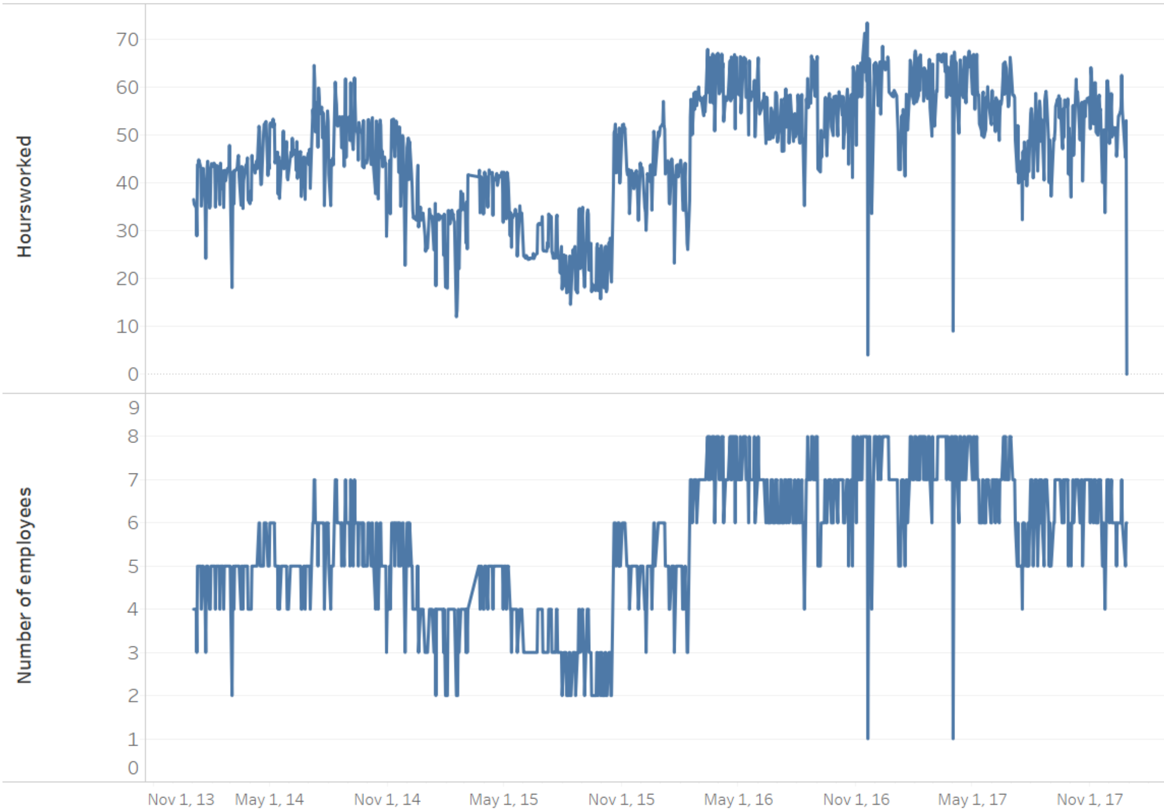


Figure 7. VICC lab staffing

We also looked at changes in staffing from the perspective of job titles. This analysis (4.a. in Table 2) is shown in figure 6. Whereas in 2014 the lab employed some phlebotomists, it appears to have switched almost entirely to using LPNs.

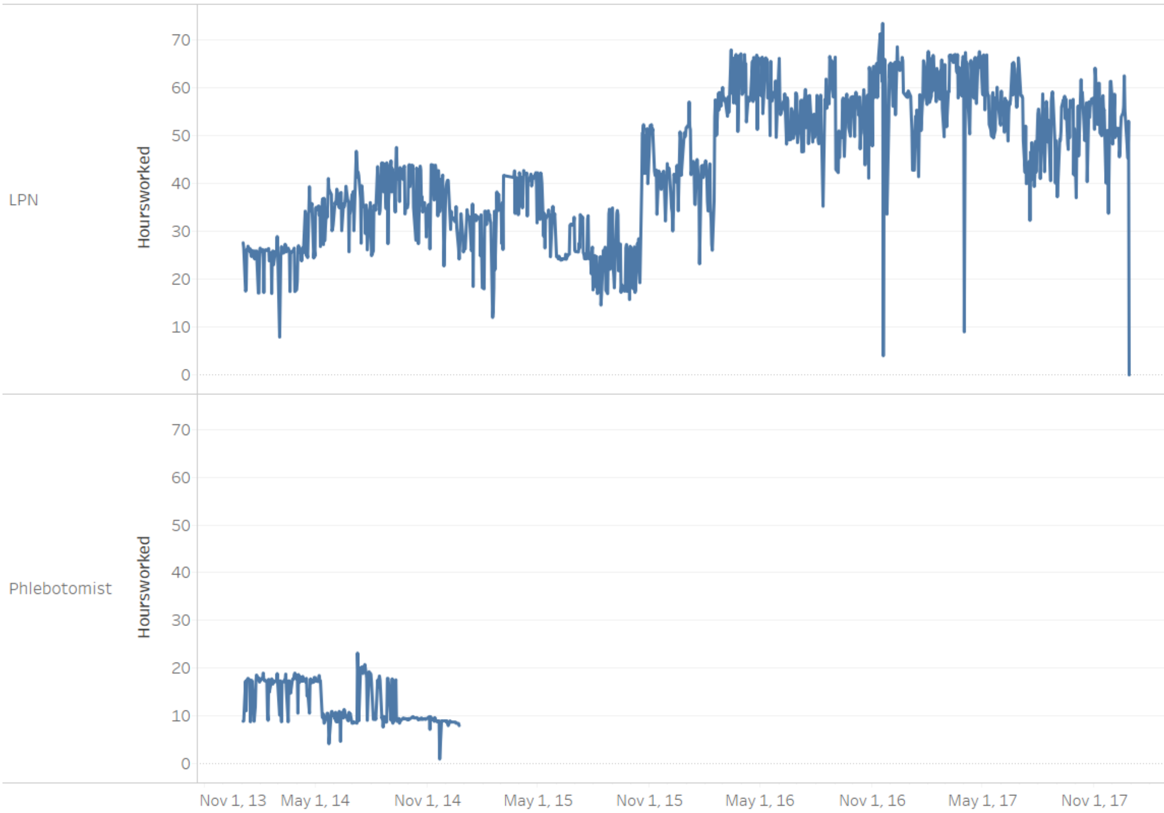


Figure 8. VICC lab staffing by job titles

We also calculated the Pearson correlation coefficient between the total number of hours worked by staff and the median time patients spent at that location to see if increased staffing correlates with shorter patient waits. The lab shows exhibits a weak negative correlation with staffing, whereas the clinic shows no correlation and the infusion area has a weak positive correlation. Table 3 shows this analysis.

Location	**Pearson Correlation Coefficient**
Lab	-0.36119371
Doc	0.054973735
Inf	0.289470932

Table 3. Pearson correlation coefficient between the total number of hours worked by non-physician staff and the median time patients spend at that location

The second reason identified by leadership was a reduction in paperwork for the registration staffing. There was no analytical data that would substantiate this claim.

Through conversations with staff during a second round of qualitative observations, two more reasons that emerged as reasons that would explain the shorter wait times at the lab were: the fact that the PSR at the lab is trying to get patients in faster even if they are early for their appointment, and a better utilization of one of the chairs(analyses 3.c. and 3.d. in Table 2). Figure 7 shows these times in minutes for all the locations of interest (room movement timestamp-appointment time) (analysis 4.c. in Table 2). We are seeing a 15% improvement in the time it takes for patients who are early for their appointment at the lab to be put in room. At the same time the number of patients early for their appointments has increased by 50%.

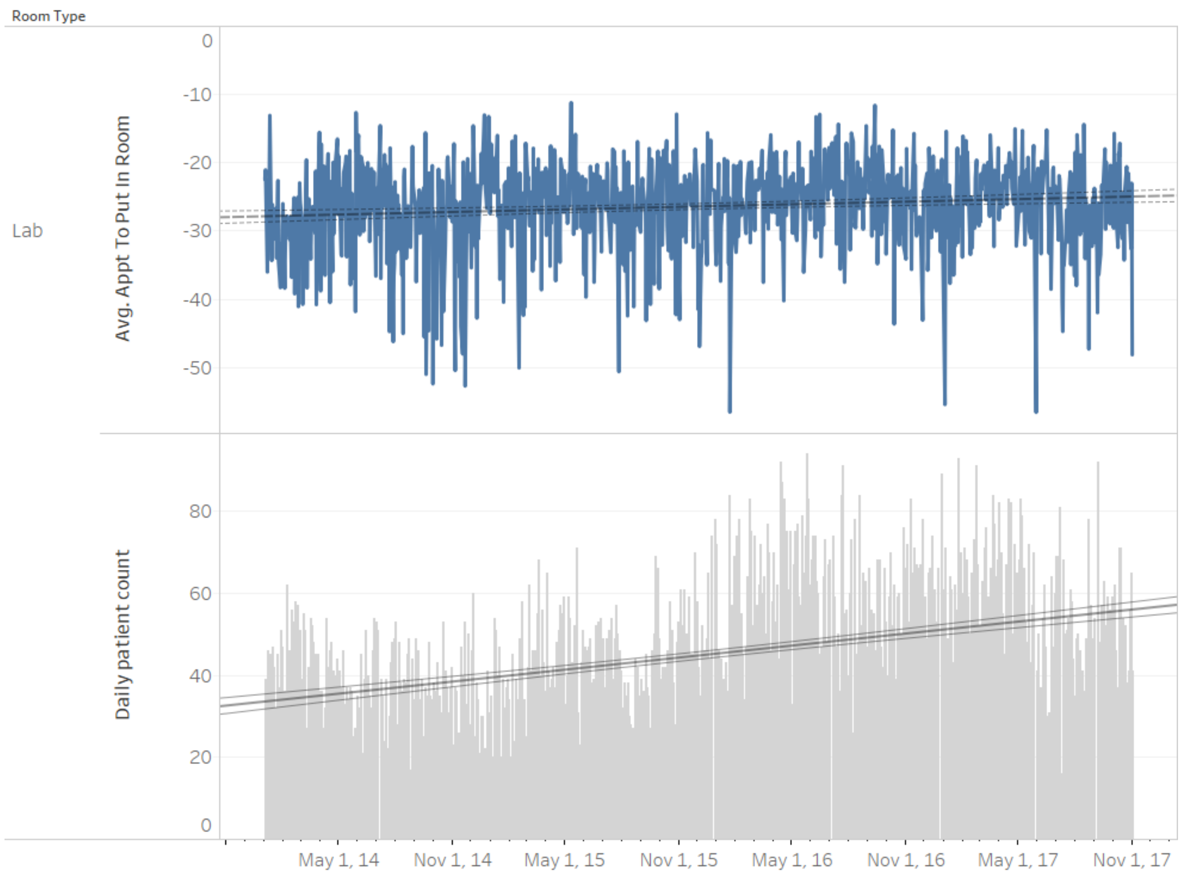


Figure 9. Average minutes between the appointment time and when the patient is put in room for patients that are early for their appointments

The second reason identified by staff for shorter wait times at the lab is a better utilization of chair 8. Figure 8 shows the cumulative total number of minutes per day each lab chair (Lab1 - Lab8) accommodates a patient (daily occupancy) and a patient count (analysis 4.d. in Table 2). Both the daily occupancy and the patient count have slightly decreased for chairs 1-5, have stayed constant for chair 6, and have increased for chairs 7 and 8. This shows a more uniform utilization of the chairs and confirms the fact that Lab8 is used more.

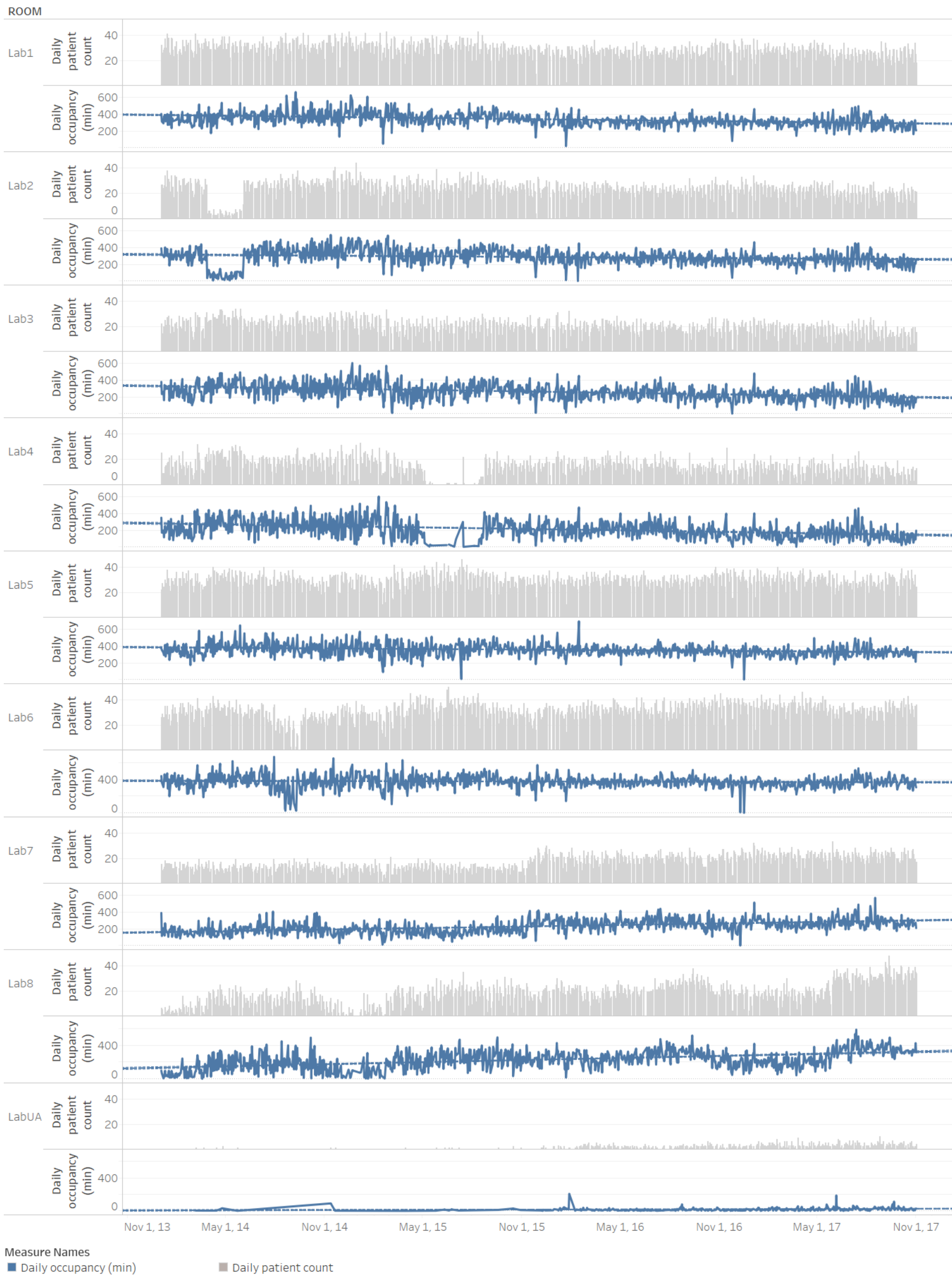


Figure 10. Total daily occupancy of the lab chairs (minutes) and the total number of patients served

Through direct observation, the researcher (ID) identified four other workflow problems (analyses 3.e., 3.f., 3.g. in Table 2). First, chair 8 did not appear to be used as much as the others due to the proximity to the door. This observation was invalidated by the chair utilization data as discussed above and shown in Figure 7.

Second, the pager system was unreliable. As a result, the registration and lab area were very noisy due to patients having to be called out. Also, patients were constantly coming to the registration desk wondering if their name had been called. The analytical data show that although the number of VICC patients increased, the number of patients being paged decreased due to a distrust by staff in the paging system (analysis 4.f. in Table 2). In addition, the time it took to respond to the page had increased and became much more variable. This is illustrated in figure 9 below.

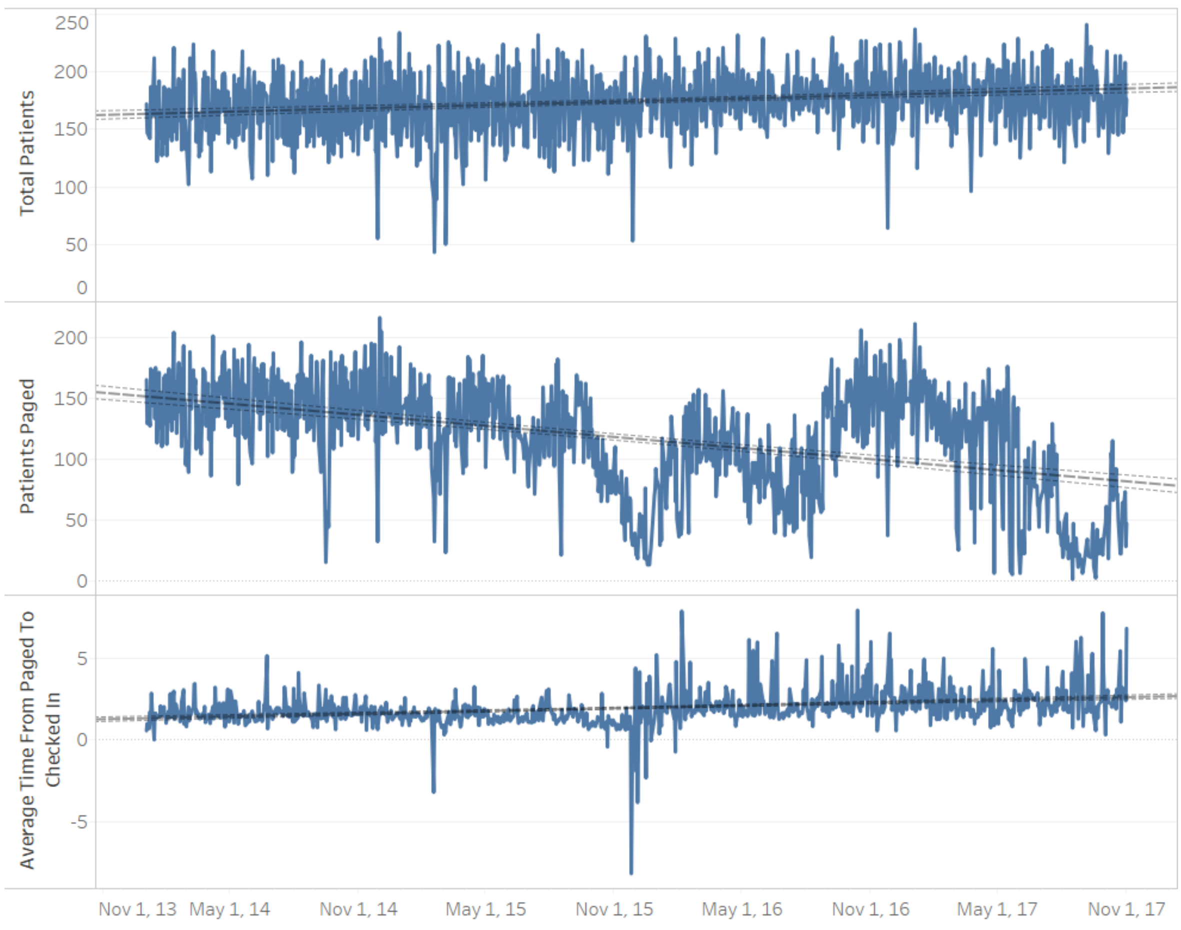


Figure 11. Total number of VICC patients, the number of patients paged and the average time it took to answer the pages

The third observation (analysis 3.g. in Table 2) indicated that patients with ports take longer due to the requirement to document the state of the port. Therefore, we investigated this claim analytically (analysis

4.g. in Table 2). The median number of minutes patients are rooms is 10% higher for patients with ports.

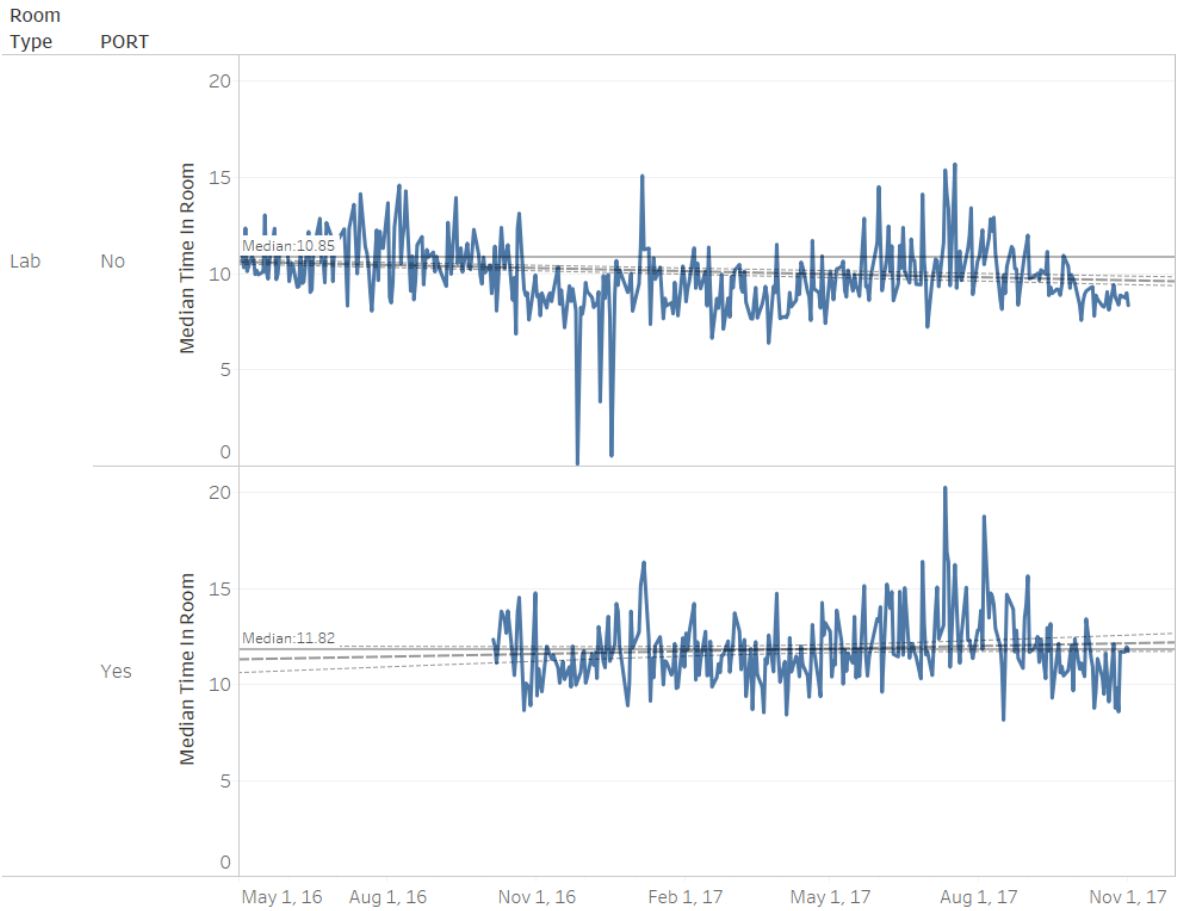


Figure 12. Median time in room for patients without ports and with ports

To investigate this hypothesis even further we also performed a T-test described in tables 4 and 5 below.

	Time in room no port	Time in room with port
Mean	11.15744113	13.00977857
Variance	67.03926477	66.00062793
Observations	40936	10116
df	40935	10115
F	1.015736772	
P(F<=f) one-tail	0.161181879	
F Critical one-tail	1.026286416	

Table 4. F-Test Two-Sample for Variances

	Time in room no port	Time in room with port
Mean	11.15744113	13.00977857
Variance	67.03926477	66.00062793
Observations	40936	10116
Hypothesized Mean Difference	0	
df	15587	
t Stat	-20.50315696	
P(T<=t) one-tail	1.66E-92	
t Critical one-tail	1.644951392	
P(T<=t) two-tail	3.31E-92	
t Critical two-tail	1.960116192	

Table 5. T-Test: Two-Sample Assuming Unequal Variances

The last element of the analysis is the side-by-side comparison between workflow information extracted from access logs and Whiteboard patient movement. Figure 11 shows this workflow timeline for the registration, lab and clinic areas located on the first floor of the VICC, while figure 12 focuses on the infusion area located on the second floor of the VICC.

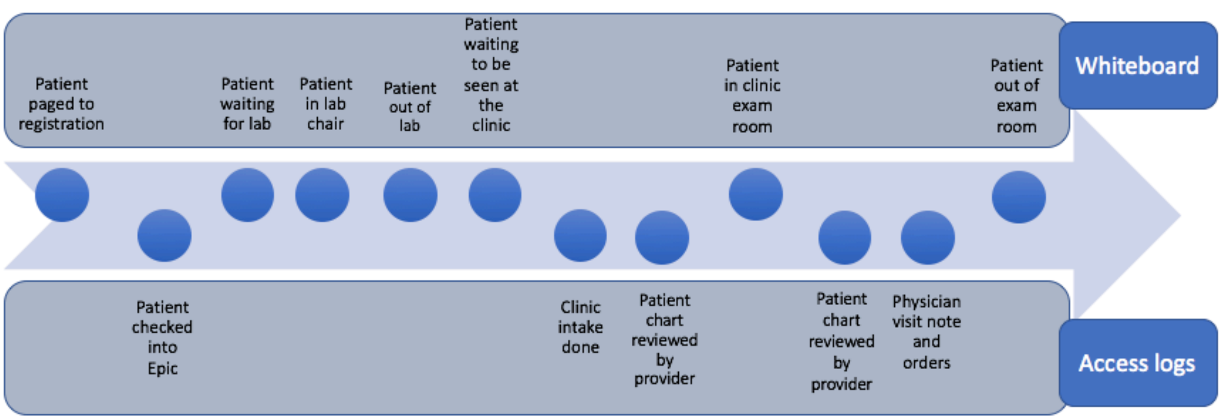


Figure 13. Workflow timeline for the VICC registration, lab and clinic area

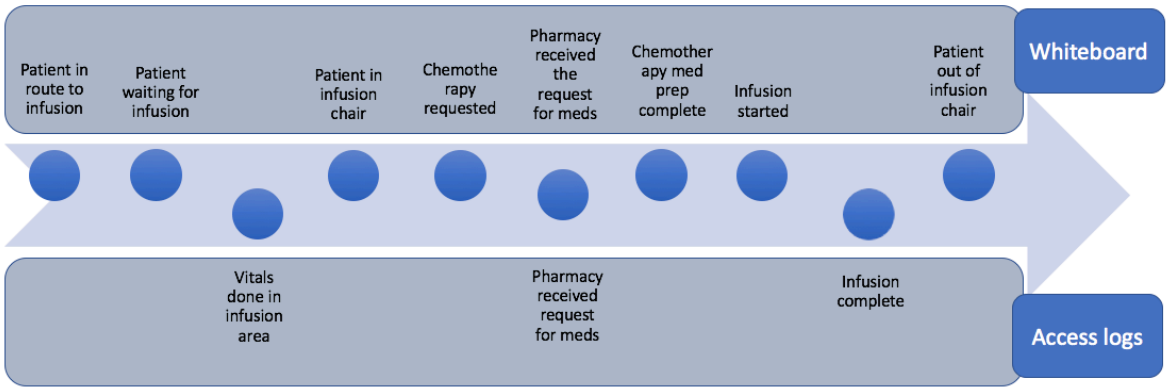


Figure 14. Workflow timeline for the VICC infusion area

The EHR access logs are an imperfect proxy for both the Whiteboard room movement and the communication pieces. The time discrepancy ranges from minutes to hours. Even the former is critical when studying workflow because certain events only take minutes.

5. Discussion

5.1 Workflow infrastructure discussion

The Outpatient Whiteboard is a big asset in our workflow analysis. Throughout our evaluation, it proved to be not only a wonderful workflow and communication tool, but also a very reliable analytical data source. In light of the new EHR implementation the Whiteboard functionality has to be taken into account when configuring the new system. Our analysis emphasizes the role and the importance of the Whiteboard as an excellent non-verbal communication system. It provides great visibility into the patient's medical journey through the VICC by aggregating complex workflow information into readily available statuses. Users could not only see only a certain set of patients like those at the lab or lab waiting room for example but they also benefited from having a series of flags for the patient that were big time savers. For example, the PSR at the lab used the wheelchair flag quite extensively to decide if she can assign a certain patient to one of the three lab chairs that were wheelchair accessible. In the absence of these flags, users have to: perform additional clicks into the EHR to gather information such as: are the labs done; perform additional work like scrolling through a long list of patients if it cannot be filtered by location; call another staff member who might have the information; or work without it, if it cannot be found elsewhere in the EHR. Either alternative is clearly a workflow disruption and is not recommended.

On the secondary use of the OPWB, data were stored very nicely in a transactional fashion, with the appropriate timestamps, making it easy to use for research. As shown in figures 11 and 12, while the EHR access logs contain some of the workflow data points, the Whiteboard remains the primary source of room movement information. While the access logs contain more data, the Whiteboard is a much "cleaner" source of workflow information. As an example, a physician might start to review a patient's chart in the morning, then again while the lab is calling to verify orders, then again right before the appointment, during the appointment and might be writing notes in the evening. It is therefore painstaking to determine when exactly did the physician actually see the patient face to face using just access logs.

In addition to the Whiteboard, we also had an EHR that records the access to its different functions, an electronic laboratory information system, an HR system that keeps track of the number of hours worked, electronic appointment scheduling, electronic nursing documentation, a computerized provider entry system and an EDW that archives the data produced by all of these systems for research and reporting. Being able to get this plethora of data electronically was a necessity for our study.

5.2 Methodology discussion

The initial qualitative assessment is a critical part of the methodology we are proposing. Firstly, it provides a connection to the environment and an opportunity for the researcher to relate to the test subjects. Secondly, it exposes the researcher to the technologies used and how these fit into the daily workflows. Thirdly, it allows an understanding of the processes in place. While some workflows might be very complex, at this phase it is important to find the right balance of detail as to be able to move relatively quickly to the next phase: quantitative data analysis.

The second phase focuses on secondary use of data generated by the EHR systems encountered in the first step. While this presents vast opportunities, it is important to focus on items that 1) are important for clinical users and or leadership and 2) can be improved. In our case, this first metric was patient wait time at the lab and the clinic, an important benchmark to leadership as it relates to VICC operational efficiency and patient satisfaction, a Center for Medicare Services reportable outcome.

In the next phase, data collected through qualitative observations and conversations with staff helps narrow down the breadth of the next step: the data analytics. Using the results to illustrate the methodology, we found that reduction in wait time observed initially could be due to better staffing in two ways. Firstly, increasing the number of workers at the lab and therefore, the numbers of hours worked to an optimal level leads to better throughput. Secondly, equalizing the job duties by employing all LPNs at the lab allows for more efficient execution of the tasks at hand. Since the lab performs both blood draws and port flushes, but LPNs have to perform the later, one can imagine a situation where before the standardization, although a phlebotomist is available, the patient would have to wait for a LPN to become available. Indeed, the Pearson correlation table 3 indicates that at the lab, increased staffing decreases the amount of time patients spend in the lab. The reason why the clinic does not experience a similar association has to do with some peculiarity of the data analyzed: the kronos system only records the hours worked for hourly staff, which physicians are not. Since they do not have to clock in and out, we cannot augment the kronos data set analytically to calculate a Pearson. In the case of the infusion center, where staff spends a small fraction of the total visit with the patient we believe the small correlation between the number of hours worked and the time spent by the patient might be purely coincidental.

In terms of capacity, the lab chairs do not see a uniform use amongst themselves and also across time. This finding suggests that improved chair utilization could reduce the time patients spend waiting for the lab and in lab even further.

The fourth phase explores analytically the qualitative trends observed in phase three. The data confirmed most of the phase three findings, namely 4.a., 4.c., 4.d., 4.f., and 4.g. in Table 2. Interestingly it invalidated the findings in 4.e. related to one of the chairs still not being used as much as others. These results reiterated the value of our methodology where findings from both the qualitative and the quantitative phases are verified using the other approach.

5.3 Methodology challenges and limitations

Our methodology presented a number of challenges and limitations. From the qualitative perspective, we had access to people that enabled our study. The VICC nursing leadership was extremely engaged and allowed us to observe the day-to-day workflow at the cancer center. They also provided us with insight and feedback on our findings. Moreover, the staff in the clinical areas were used to having students be present during their interactions with the patients, minimizing disruptions to workflow. Not being able to operate in a similar environment would definitely hinder the qualitative studies.

From a data analytics standpoint, our method benefited greatly from having electronic tools such as the Outpatient Whiteboard that generated patient room movement and communication logs. These data were well timestamped, and required minimal cleanup. We also benefited from having an entire ecosystem of other electronic data sources: human resources, appointment scheduling, lab, etc. that we could combine in our analytics investigations. These data were stored in a single source, an enterprise data warehouse, that was a one-stop-shop for all the data needs. Lastly, it was important that access to the data was granted in a timely manner such that the analyses could be completed. The absence of any of these factors would have constituted major road blocks in our demonstration of the methodology.

5.4 Methodology advantages

An aspect of EHR data analysis has to do with the vast amounts of data produced and available for research. Our method proposes an investigation informed by the environment as a solution to the needle in the haystack problem. The analysis shown in Figure 7 illustrates this point. Without the prior knowledge of the fact that the lab tends to get patients in as quickly as possible, we might not be comparing the appointment time with the time patients where actually put in the room, which is an interesting analysis in its own.

The paging problem identified during the third phase-qualitative analysis is another perfect illustration why the analysis informed by the environment method is more successful than either quantitative or qualitative data analysis alone. The fact that the page is not received by the physical pager is not recorded by any data source. Through qualitative observations and conversations with staff though, we know that both staff and patients have lost confidence in the fact that the paging system works, and that patients are taking longer to respond due. These two observations that can be substantiated by EHR data analyses allowed us to quantify the size of the paging problem. In the EHR data we are seeing a sharp decrease in the number of patients paged between 2014 and now. We are also seeing an increase in the time it takes patients to respond to pages and the variability of these time intervals. These two data analyses show a pretty significant problem with the paging system. Surprisingly, the leadership was not fully aware of the magnitude of this issue so being able to review the data was significant for them and allowed them to allocate further resources to probe the situation further.

The port analysis shows once again that the quantitative data alone does not explain the why behind it. Patients with ports take slightly longer on average due to the fact that the port access additional documentation. Blood draws through the port however might lower this average because LPNs do not have to search for the vein.

Quantitative analyses on the other hand can confirm or deny qualitative findings. That is because they can systematically analyze data over longer time periods. Our study period spanned a three and a half year time period, which would have not been feasible to study just qualitatively. The quantitative analysis also allowed us to focus the qualitative observations on specific areas. As such, after observing a decreasing wait time at the lab and clinic, we were able to observe in these two specific areas, which reduced the qualitative study time substantially.

5.5 Methodology metrics

Mixed methods involving qualitative and quantitative approaches are hard to quantify because the two methods have very different premises. Our method did result in a number of improvements over each method used alone. Overall, our iterative approach of creating quantitative data analyses based on a good understanding of the environment resulted in time savings. The qualitative observations added just 42 additional hours to the study, but probably saved the research team at least that long, time that would have been spent doing data detective work. Moreover, once the researchers have familiarized themselves with the clinical processes at each of the locations, subsequent observation episodes became much more expedited. Our last round of observations (3 hours) proved that even the implementation of a new EHR did not substantially increase the follow-up observation time: identifying changes brought on by the new technology is straight forward if the researcher had already familiarized themselves with the clinical area. The qualitative side also saw an efficiency improvement using our approach. Adding the EHR data allowed us to systematically analyze workflow trends over a three-and-a-half-year period without dedicated researchers observing the entire time.

Looking at how data analytics refutes or confirms trends obtained in the qualitative phase is another way to quantify the performance of the mixed methods approach. Using our method, we were able to validate most of the qualitative observation trends but also disprove one of the items.

Qualitative studies on the other hand reduce the amount of data used by the quantitative analysis, which is another quantifiable metric. As such, to investigate the reasons for the wait time decreases at the lab we were able to focus on OPWB patient movement and patient pager data, EPIC appointment scheduling, Kronos timesheet data, HR information and EHR access logs. We did not use lab data, any other EHR data, OPWB infusion status communication, nursing documentation, barcode medication administration data, etc. By pruning the amount of data used, our method is able to reduce the computation time.

Our method also provided more informed insight for the VICC nursing leadership. The qualitative studies revealed complexities such as the malfunctioning of the paging system of which the leadership was not fully aware. The analytics helped quantify the size of these problems which empowered the leadership to be more informed decisions. This metric is harder to quantify numerically, because the benefits are intangible.

5.6 Methodology recommendations

Both the qualitative observations and the data analysis revealed that OPWB was a great asset for our workflow analysis. Having a dedicated tool can improve both the efficiency of the clinical staff and the workflow researchers, on the secondary use side. We strongly recommend having a tool that supports clinical processes and communication in the same way and also store the information in a neat way that can be used for research with minimal cleanup.

Secondly, we recommend using a sequential approach of qualitative and quantitative phases. This way, each method can be informed by the previous step and provide a starting point for the next.

Thirdly, when using a similar mixed methods approach to understand clinical workflow, we recommend starting with a qualitative phase. This allows the researcher to be immersed in the environment and understand the clinic priorities and how the technologies they use fit in.

Our qualitative studies used a number of techniques to validate the findings from triangulation to prolonged exposure in the field to peer debriefing. Being able to confirm the validity of the observational process adds rigor to the qualitative phase but also to the mixed methods approach as a whole.

6. Conclusion

Our multiple iteration mixed-method analysis provides a better approach to just quantitative or qualitative data analytics alone. Analytical data will never be perfect nor will never capture everything so it relies on qualitative data to explain why people are doing tasks in a certain order for example. At the same time, qualitative data analysis is very time consuming and very dependent on factors outside of the control of the researcher such as willingness of the participants to allow the observation and engage in conversations with the researchers. It therefore benefits greatly from the pairing with the systematical data approach. Given the utility of the Outpatient Whiteboard in the context of our analysis methodology, one future opportunity consists of repeating the evaluation using the Whiteboard replacement in the new EHR. Another direction for future work is to create a statistical model that measures the contribution of each of our findings to the overall outcome. Establishing a protocol for measuring the performance of the mixed methods is another possibility for future studies.

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