Identifying Complex Scheduling Patterns Amongst Cancer Patients with Transportation and Housing Needs

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Table of Contents

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Abstract

Background: Cancer patients frequently encounter complex treatment pathways, often characterized by challenges with coordinating and scheduling appointments at various specialty services and locations. Identifying patients who might benefit from scheduling and social support from community health workers (CHW) or patient navigators is largely determined on a case-by-case basis and is resource intensive.

Objective: Our study proposes a novel algorithm to use scheduling data to identify complex scheduling patterns amongst patients with transportation and housing needs.

Methods: We present a novel algorithm to calculate scheduling complexity from patient scheduling data. We define patient scheduling complexity as an aggregation of sequence, resolution, and facility components. We apply the scheduling complexity algorithm to 38 breast cancer patients' scheduling data and compare this metric with common count-based metrics.

Results: Five patients exhibited high scheduling complexity with low count-based adjustments. Two patients exhibited high count-based adjustments with low scheduling complexity. Of the 15 patients that indicated transportation or housing insecurity issues in conversations with CHWs, 86.7% (13 of 15) patients were identified as medium or high scheduling complexity while 60% (9 of 15) were identified as medium or high count-based adjustments.

Conclusions: Scheduling complexity identifies patients with complex, but non-chronical scheduling behaviors who would be missed by traditional count-based metrics. This study shows a potential link between transportation and housing needs with schedule complexity. Scheduling complexity can complement count-based metrics when identifying patients who might need additional care coordination support especially as it relates to transportation and housing needs. Clinical Trial: NA

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ABSTRACT

Objective

Cancer patients frequently encounter complex treatment pathways, often characterized by challenges with coordinating and scheduling appointments at various specialty services and locations. Identifying patients who might benefit from scheduling and social support from community health workers (CHW) or patient navigators is largely determined on a case-by-case basis and is resource intensive. Our study proposes a novel algorithm to use scheduling data to identify complex scheduling patterns amongst patients with transportation and housing needs.

Methods

We present a novel algorithm to calculate scheduling complexity from patient scheduling data. We define patient scheduling complexity as an aggregation of sequence, resolution, and facility components. We apply the scheduling complexity algorithm to 38 breast cancer patients' scheduling data and compare this metric with common count-based metrics.

Results

Five patients exhibited high scheduling complexity with low count-based adjustments. Two patients exhibited high count-based adjustments with low scheduling complexity. Of the 15 patients that indicated transportation or housing insecurity issues in conversations with CHWs, 86.7% (13 of 15) patients were identified as medium or high scheduling complexity while 60% (9 of 15) were identified as medium or high count-based adjustments.

Discussion

Scheduling complexity identifies patients with complex, but non-chronical scheduling behaviors who would be missed by traditional count-based metrics. This study shows a potential link between transportation and housing needs with schedule complexity.

Conclusion

Scheduling complexity can complement count-based metrics when identifying patients who might need additional care coordination support especially as it relates to transportation and housing needs.

INTRODUCTION

Cancer patients frequently encounter complex treatment pathways, often characterized by challenges with coordinating and scheduling appointments at various specialty services and locations [1-3]. Previous studies have shown that the burden of scheduling and attending visits across multiple providers and specialties not only burdens patients, but also has ripple effects on families, work, and personal lives [4 5]. To address challenges around scheduling appointments, some healthcare institutions employ individuals such as Community Health Workers (CHWs) or patient navigators, who play a pivotal role in guiding cancer patients through their care journey [6]. CHWs and patient navigators have a wide variety of skills and can provide critical assistance coordinating appointment scheduling and overcoming barriers to attending care [4 7 8]. Patients who might benefit from this additional assistance are largely identified manually by CHWs or by care providers aware of possible challenges and social needs [9], or some clinics may assign all patients to CHWs, a resource intensive process [10-12]. Workflows reliant on staff to identify those who might benefit the most from navigation can be time-consuming and resource-intensive, making it difficult to comprehensively identify patients in need of assistance. While ideally all patients would be offered navigation services, in light of staffing shortages and overall limited patient navigation resources, many institutions may be limited in who they can provide extra supportive services to [13].

Our study used existing scheduling data to identify patients with complex scheduling patterns which may be influenced by unmet social needs in transportation and housing. We introduce a novel algorithm to quantify the complexity of a patient's scheduling data derived from a parent study with CHWs supporting breast cancer patients with comorbidities during cancer treatment. Then, we applied the algorithm to 38 breast cancer patients' scheduling data. The resulting scheduling complexities are compared to count-based metrics and call notes between CHWs and patients to identify unmet transportation or housing needs.

BACKGROUND

Navigating complex schedules in cancer care

Patients with cancer experience treatment and scheduling complexities associated with needing to maintain complicated and changing treatment regiments, managing multiple appointments at multiple locations within hours or days of each other, and coordinating care across clinics (e.g., medical oncology, cardiology, plastic surgery, physical therapy) [4 5 8 14]. In one study, scheduling complexities were the most chronic issues for cancer patients [14]. These complexities are difficult to navigate for patients, and can impact their family, work, and personal lives [4 5 8]. In addition, oncology clinics experience a high rate of no shows and cancellations, without fully capturing data on reasons for non-attendance. In response to appointment scheduling complexities, some clinics require CHWs and patient navigators to have a wide variety of skills to help guide cancer patients through the complexities of cancer and target patients from underserved populations [7]. One critical service CHWs and patient navigators provide is coordinating appointment scheduling to reduce patients' complexity of care [4 8].

Challenges with identifying patients with needs

Scheduling complexities do not fall on all patients equally. Patients facing social inequalities – such as unequal access to transportation, housing, and/or social support – face additional complexities in their cancer care appointments. For instance, cancer patients without insurance, indicating financial vulnerability, are at high risk of no-show appointments [15 16]. Qualitative data indicate that low-income patients, especially low-income women, face barriers to maintaining follow-up appointments due to work, childcare, and caregiving responsibilities [17 18]. Because people subjected to social inequities often have scheduling complexities, identifying such complexities could be a way for

CHWs to identify in-need patients. Currently, social needs are not consistently and comprehensively assessed in oncology settings, and there is no standard way that cancer patients are flagged for assignment to a CHW or patient navigator. Some clinics may automatically assign all cancer patients to CHWs or patient navigators, whereas others attempt to target patients who are at highest need for help navigating cancer care [7]. Furthermore, there is no universal adopted screening tool to identify high need patients [9 19]. A data-driven solution that alleviates burden from support staff (i.e., reviewing charts to identify patient needs) or relying on clinician referrals would be ideal to effectively and efficiently allocate limited CHW and patient navigator resources.

Potential of scheduling data

One potential way to identify patients with unmet transportation or housing needs is to utilize scheduling data to examine who is experiencing high scheduling complexities. Scheduling data for most cancer care is electronic, providing detailed data about when appointments are scheduled, cancelled, rescheduled, or no shows. This data is automatically recorded, and thus could be utilized to identify patients who are struggling to manage the complexity of cancer care.

In past research, appointment data has primarily been used to optimize appointment scheduling for patient satisfaction and resource allocation [20-23]. Analyses tend to focus on developing and testing scheduling methods to best balance patient satisfaction (e.g., wait times) with clinic resources. For example, using model simulations to optimize the scheduling of oncology visits and chemotherapy treatments [21], or optimizing scheduling rules based on chemotherapy infusion [23]. Other research using scheduling data examines the efficiency of appointment self-scheduling processes [24], optimizing scheduling for cost savings [22], and identifying ways to reduce wait times for patients [20]. One study designed an algorithm that used appointment data to identify patients' primary care physician [25]. However, to our knowledge, researchers have yet to design tools for analyzing scheduling data to identify patients with possible unmet transportation or housing needs during their cancer care.

CONTRIBUTIONS

We present a novel algorithm to calculate scheduling complexity from scheduling data. Scheduling complexity is an aggregation of sequence, resolution, and facility components. Each component is motivated by the characteristics of scheduling data, an appointment's anatomy, and possible outcomes. The scheduling complexity algorithm is then applied to 38 breast cancer patients' scheduling data as a case example. The resulting scheduling complexities are compared to count-based metrics and call notes between CHWs and patients to identify unmet transportation or housing needs.

METHODS

Anatomy of an appointment

Every appointment has a unique appointment ID (AID) and is *scheduled on* a specific date and time and *scheduled for* a specific date, time, and location. An appointment is scheduled for a specific visit reason and is associated with the corresponding visit ID (VID). Typically, one date will have one appointment scheduled with one associated VID, Figure 1 (top). Sometimes there can be multiple appointments with different VIDs scheduled for the same date. This is illustrated in an example patient schedule in Table 1. An MRI and mammogram are both scheduled for 1/15/23. The MRI and mammogram appointments have different AIDs (AID-5 and AID-6 respectively) and VIDs (VID-4 and VID-5 respectively) because they have different reasons for visit and will be at different locations, one on the ground floor and one on the second floor of the hospital. There can also be multiple AIDs for different dates associated with the same visit reason and at the same location, VID,

Figure 1 (bottom). A common example of this pattern is for daily treatments as illustrated in Table 1. There are four appointments for the same treatment at the same location with the same VID (VID-7) but with different AIDs (AID-9, AID-10, AID-11 and AID-12). All the AIDs are for the same treatment and at the same location and would have the same VID.

Table 1: Example individual patient scheduling temporal pattern

VID	AID	Reason for Visit	Location	Scheduled on	Scheduled for	Cancelled on	Rescheduled on	Arrived on
VID-1	AID-1	New consult	Hospital A - 2nd FL	1/1/2023	1/5/2023			1/5/2023
	AID-2	Colon screening	Hospital B - Ground	1/1/2023	2/1/2023	1/17/2023		
VID-2	AID-3	Skin check	Hospital B - Ground	1/3/2023	1/10/2023			1/10/2023
VID-3	AID-4	Echocardiogram	Hospital A - Ground	1/5/2023	1/20/2023			1/20/2023
VID-4	AID-5	C50.912 MRI	Hospital A - Ground	1/10/2023	1/15/2023			1/15/2023
VID-5	AID-6	LF Breast Mass - Mammo	Hospital A - 2nd FL	1/15/2023	1/15/2023			1/15/2023
VID-6	AID-7	Follow up	Hospital A - 2nd FL	2/1/2023	2/20/2023		2/10/2023	
VID-6	AID-8	Follow up	Hospital A - 2nd FL	2/10/2023	2/25/2023			2/25/2023
VID-7	AID-9	Treatment	Infusion center - 2nd FL	4/1/2023	4/5/2023			4/5/2023
VID-7	AID-10	Treatment	Infusion center - 2nd FL	4/1/2023	4/6/2023			4/6/2023
VID-7	AID-11	Treatment	Infusion center - 2nd FL	4/1/2023	4/7/2023			4/7/2023
VID-7	AID-12	Treatment	Infusion center - 2nd FL	4/1/2023	4/8/2023			4/8/2023

Appointment action outcomes

In our data, there were four possible action outcomes for an appointment: arrived, rescheduled, canceled, or no show as illustrated in Figure 2. Arrived is the most common action outcome in which the patient arrives on the scheduled appointment date. Rescheduled occurs when the appointment needs to be rescheduled for another date. This can be due to multiple reasons such as patient's preference, medical necessity, financial or transportation issues, circumstances or system related factors such as being bumped, unresolved insurance authorization, etc. Rescheduling an appointment will result in a new AID. An appointment can also be canceled by the patient or the hospital. For example, in our data, a provider could be unavailable due to illness or a scheduling conflict. Similar to rescheduled, canceled appointments can be caused by a variety of patient or hospital system reasons. Lastly, no show occurs when a patient doesn't arrive to an appointment and does not cancel the appointment.

Sources for scheduling complexities

Sequence complexity: Appointment ordering sequence

We define schedule sequence complexity as the degree to which appointments are scheduled and arrived to in non-chronical order. While there are several ways to define temporal complexities, we choose a queuing approach as it most closely aligns with patient scheduling experience [26 27]. As such schedules with low sequence complexity are those where appointments are scheduled and arrived in chronical order. This follows the general queuing rule of *first in-first out*: appointments scheduled first are arrived to first which minimizes the number of outstanding appointments at any given time. Schedules with more sequence complexity are those where appointments are scheduled and arrived to not in chronical order. Using the illustration in Table 1, AID-1 and AID-3 are examples of appointments scheduled and arrived in chronical order. AID-1 is scheduled before AID-3 and AID-1 is arrived to before AID-3. AID-4 and AID-5 are examples of appointments scheduled and arrived in non-chronical order. AID-4 is scheduled before AID-5 but the patient arrived to AID-5 before AID-4. This complexity can be caused by many factors such as appointments scheduled for the far future, canceling and rescheduling of appointments, or emergent appointments. These factors can increase schedule challenges both for the patient and scheduling systems.

Resolution complexity: Unresolved appointments

No shows or canceled appointments without rescheduling or reason can increase scheduling complexity in a patient's care. Missing appointments leads to increase patient risk for cancer recurrence and mortality [28 29], and inefficiency for the healthcare system including lost revenue [30 31]. These unresolved appointments have no resolution, leaving uncertainty about potential delays in treatment and care. However, there are sometimes canceled appointments because of changes in treatment plans or no shows that are resolved through another action. Actions for these resolved appointments often co-occur with action dates for arrived or rescheduled appointments. Hence, we define resolution complexity as the number of no shows or canceled appointments on dates that do not co-occur with other action dates divided by the total number of no shows or canceled appointments.

Location complexity: Appointments at multiple facilities

Having care at multiple facilities or locations can also increase scheduling complexities as this usually means more coordination and travel between facilities. Intuitively, a schedule with lower location complexity will have fewer facilities for care on the same day. A schedule with higher location complexity will more often require the patient to attend different facilities for care on the same day. Location complexity is calculated as the number of arrived dates involving two or more different locations divided by the total number of arrived dates.

Calculating scheduling complexity

The algorithm for calculating a schedule's scheduling complexity is described below. First, schedule data is separated into arrived and not arrived appointments, ARRIVED and NONARRIVED respectively. ARRIVED appointments are aggregated at the date level. For each AID in ARRIVED, if there exist other AIDs with scheduled on dates preceding the current AID's scheduled on date and these subsequent appointments were attended after the current AID's date, then the count of out-of-order occurrences is increased. Sequence complexity is calculated as the ratio of out-of-order counts to the total count of distinct arrived dates in ARRIVED. Next, for each AID in NONARRIVED group, an action date is determined, representing the date when an appointment was either canceled, bumped, or scheduled but resulted in a no-show. If this action date does not appear in the dataset of ARRIVED appointments, then the count of unresolved cases is increased by one. Resolution complexity is then computed as the ratio of unresolved counts to the total count of AIDs within the NONARRIVED group. Location complexity is calculated as the number of arrived dates in ARRIVED involving two or most different locations divided by the total number of arrived dates in ARRIVED. Lastly, a composite metric scheduling complexity is the harmonic mean of sequency complexity, resolution complexity, and location complexity.

ALGORITHM: Deriving scheduling complexity

```
ARRIVED, NONARRIVED ← Separate data into arrived and not arrived appointments

For each AID in ARRIVED:
    If there are other AID date that was made before current AID date and arrived to after current AID date
        Out of order count += 1
sequence complexity = out of order count / total count of unique arrived to dates in ARRIVED

For each AID in NONARRIVED:
    Action date = canceled or bumped date or scheduled date for no-show
    If Action date not in Arrived_data:
        unresolved += 1
resolution complexity = unresolved count / total count of nonArrived AIDs

For each arrived date with multiple AIDs in ARRIVED
    If AIDs are at different locations:
        Location count += 1
location complexity = location count / total number of arrived dates with multiple AIDs in ARRIVED

scheduling complexity = 3 / (1/sequence complexity + 1/resolution complexity + 1/facility complexity)
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Case example

To evaluate the utility of scheduling complexity, we calculate the scheduling complexity for 38 breast cancer patients with hypertension or diabetes, as part of a larger health disparities project to support Black cancer patients with comorbidities via mHealth and CHW support. For this pilot evaluation, we use one year of scheduling data for each patient starting from their date of diagnosis. Sequence complexity, resolution complexity, location complexity, and scheduling complexity was calculated for each patient separately. In addition, we calculated count-based metrics: arrived ratio, rescheduled ratio, canceled ratio, and no show ratio. We define an aggregated count-based adjustment metric as the harmonic mean of rescheduled ratio, canceled ratio, and no show ratio. Count-based adjustments and scheduling complexities are stratified using quartiles and compared. We stratify patients into high, medium, and low complexities using the upper quartile, middle quartiles, or lower quartiles respectively. We compared our scheduling complexity metric to count-based adjustments because they are commonly used in first order analysis of scheduling data.

RESULTS

Schedule descriptives

The 38 breast cancer patients had a median of 88 unique AID (interquartile range, IQR = 60.3), 62 arrived appointments (IQR = 47.8), 13 rescheduled appointments (IQR = 13.5), 9 canceled appointments (IQR = 10.0), and 1.5 missed appointments (IQR = 5). The median non arrived ratio was 0.304 (IQR = 0.161). The median rescheduled ratio was 0.154 (IQR = 0.080). The median canceled ratio was 0.098 (IQR =0.081) and the median no show ratio was 0.019 (IQR =0.049), Figure 3. The median sequence complexity was 0.200 (IQR = 0.100), Figure 4. The median resolution complexity was 0.372 (IQR = 0.398). The median location complexity was 0.464 (IQR = 0.371). Lastly, the median scheduling complexity was 0.239 (IQR = 0.173).

Comparison of count-based adjustments to scheduling complexity

There was no statistically significant difference in count-based adjustments and scheduling complexity bins (X2 = 6.296, p = 0.178). The count-based and scheduling complexities were the same for 16 patients, 11 of which had both medium scheduling and count-based complexities, Table 2. Five patients exhibited high scheduling complexity with low count-based adjustments and two patients who exhibited high count-based adjustments with low scheduling complexity.

Table 2: Correlation of scheduling and count-based complexities binned by low, medium, and high

		Count-based adjustments		
		Low	Medium	High
Scheduling complexity	Low	3	5	2
	Medium	2	11	5
	High	5	2	3

In addition, Figure 5 that gives examples of schedule patterns when the count-based and scheduling metrics agreed and disagreed. Patient A has both low count-based and scheduling complexities. Patient A's schedule is a good example of appointments following the first-in first-out pattern, that is appointments scheduled first will be arrived to first. In addition, Patient A only had three rescheduled appointments. Patient B has high count-based adjustments but low scheduling complexity. 40% (8/20) of Patient B's AID were rescheduling actions which likely contributing to a high count-based adjustments. However, Patient B had low scheduling complexity because these rescheduling actions occurred only on two separate days and followed a first-in first-out sequence. Patient C has low count-based adjustments and high scheduling complexity. Although Patient C has few rescheduling actions (resulting in a low count-based adjustments), her appointments are largely scheduled and arrived to not in chronical order (resulting in a high scheduling complexity). Patient D has both high count-based and scheduling complexities. In addition to non-chronical ordering of action, Patient D had two canceled and one no show appointment action outcomes.

Context from call logs: Transportation and Housing needs

A detailed examination of call logs between patients and CHWs revealed several issues around social needs, including concerns related to advocating for tenant rights, extensive travel requirements, home repair needs, a demanding work schedule, safety concerns during metro travel, transportation challenges, complexities with an eye surgery, and the additional responsibility of caring for an ill mother. 15 patients specifically indicated transportation or housing insecurity issues. Transportation concerns included “legally blind and worried about metro access,” “[patient] feeling unsafe on metro,” “transportation challenges to and from appointments,” “making medical transportation rides,” and “needing transportation assistance.” Housing concerns included “help with finding affordable housing options,” “[patient] moving in with relative for a few months to save money,” “having to find temporary housing while home is being repaired,” “help finding rental assistance programs”. Scheduling complexity was more sensitive to housing and transportation needs. 86.7% (13 of 15) of patients specifically indicated transportation or housing insecurity issues were identified as medium or high scheduling complexity compared to 65.2% (15 of 23) of patients who did not specifically indicate transportation or housing insecurity issues. On the other hand, 60% (9 of 15) of patients specifically indicated transportation or housing insecurity issues were identified as high with count-based adjustments compared to 82.6% (19 of 23) of patients who did not specifically indicate transportation or housing insecurity issues.

Table 3: Percentage of patients with medium or high complexities by transportation or housing insecurity needs

Complexity type	Indicated transportation or housing needs	Did not indicate transportation or housing needs
Count-based adjustments	60.0% (9/15)	82.6% (19/23)
Scheduling complexity	86.7% (13/15)	65.2% (15/23)

DISCUSSION

Scheduling complexity utility

Scheduling complexity stratification provides a novel lens to complement traditional count-based metrics for analyzing scheduling data. The results show that scheduling complexity can identify patients with complex but non-chronical scheduling behaviors missed by traditional count-based metrics. In addition, the study highlights that resolution and location complexity can also serve as an indicator for additional care requirements.

Social needs and schedule complexities

This study shows a potential link between transportation and housing needs with schedule complexity. This study reinforces prior research relating social risk factors and schedule complexities [4 16]. Our results complement these findings as it relates to transportation and housing needs and highlights the potential utility of the scheduling complexity algorithm to identify patients who might benefit from additional CHW support. Through earlier identification from CHWs, scheduling complexity could help narrow inequities in cancer-care which emerge from social needs. Future studies are needed to better understand temporal sensitivity of this approach, or how quickly in-need patients could be identified.

Support for CHW and Patient Navigators

By examining the temporal patterns of healthcare utilization, we gain a more comprehensive view of patients' experiences. Instead of relying solely on infrequent screeners, scheduling complexity can give CHWs and patient navigators a more ‘real-time’ view of patients who might require more support in managing their healthcare journey, for example patients with changing, complex, and distributed care and changes in living conditions or social needs. In addition, scheduling complexity could also be used to identify care plans that might involve more complexity and preemptively identify patients that might need more support. This data-driven approach can help complement the often manual process for identifying patients who might benefit from additional assistance, potentially affording CHWs and patient navigators more time to directly care and help patients [9]. Additional research is needed to evaluate the utility of this algorithm in near 'real-time' applications for CHWs.

Limitations

This research is constrained by its retrospective analysis design, relying on historical data and records. The study exclusively focuses on the scheduling system of a single cancer institute. Sequence, resolution, and location complexity are currently weighted equally in the algorithm. However, these components might require different weights depending on circumstances. For example, for cancer care at integrated cancer centers, location complexity would probably be less important than sequence and resolution complexities. While this approach facilitates an in-depth exploration of scheduling complexity, its generalizability to other healthcare systems will need to be explored. While this approach offers valuable insights, it does not fully capture the entirety of factors that contribute to scheduling intricacies, such as resource allocation, patient preferences, and staff availability. This method could complement other approaches such as patient and scheduler interviews.

CONCLUSION

Patients facing complex healthcare journeys often experience significant impacts on various aspects of their lives, including family dynamics and work commitments. In this study, we explored the application of scheduling complexity as a complement to count-based adjustments, and its potential utility in identifying patients who might need care coordination support especially as it relates to transportation and housing needs.

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Competing Interests Statements
The authors have no completing interests to declare.

Data Availability Statement
The data underlying this article cannot be shared publicly due to appointment scheduling privacy of the cancer patients. The data will be shared on reasonable request to the corresponding author.

Contributorship Statement
All authors have made substantial contributions to the interpretation of the data, and the drafting, revising, and approval of the work. Allan Fong has made substantial contributions to the conception, design of the work, and the acquisition, analysis, and interpretation of the data. Christian Boxley has made substantial contributions to the acquisition, analysis, and interpretation of the data. Laura Schubel has made substantial contributions to the conception, design of the work, and the interpretation of the data. Christopher Gallagher has made substantial contributions to the conception, design of the work, and the interpretation of the data. Katarina AuBuchon has made substantial contributions to the interpretation of the data. Hannah Arem has made substantial contributions to the conception, design of the work, and the acquisition, analysis, and interpretation of the data.

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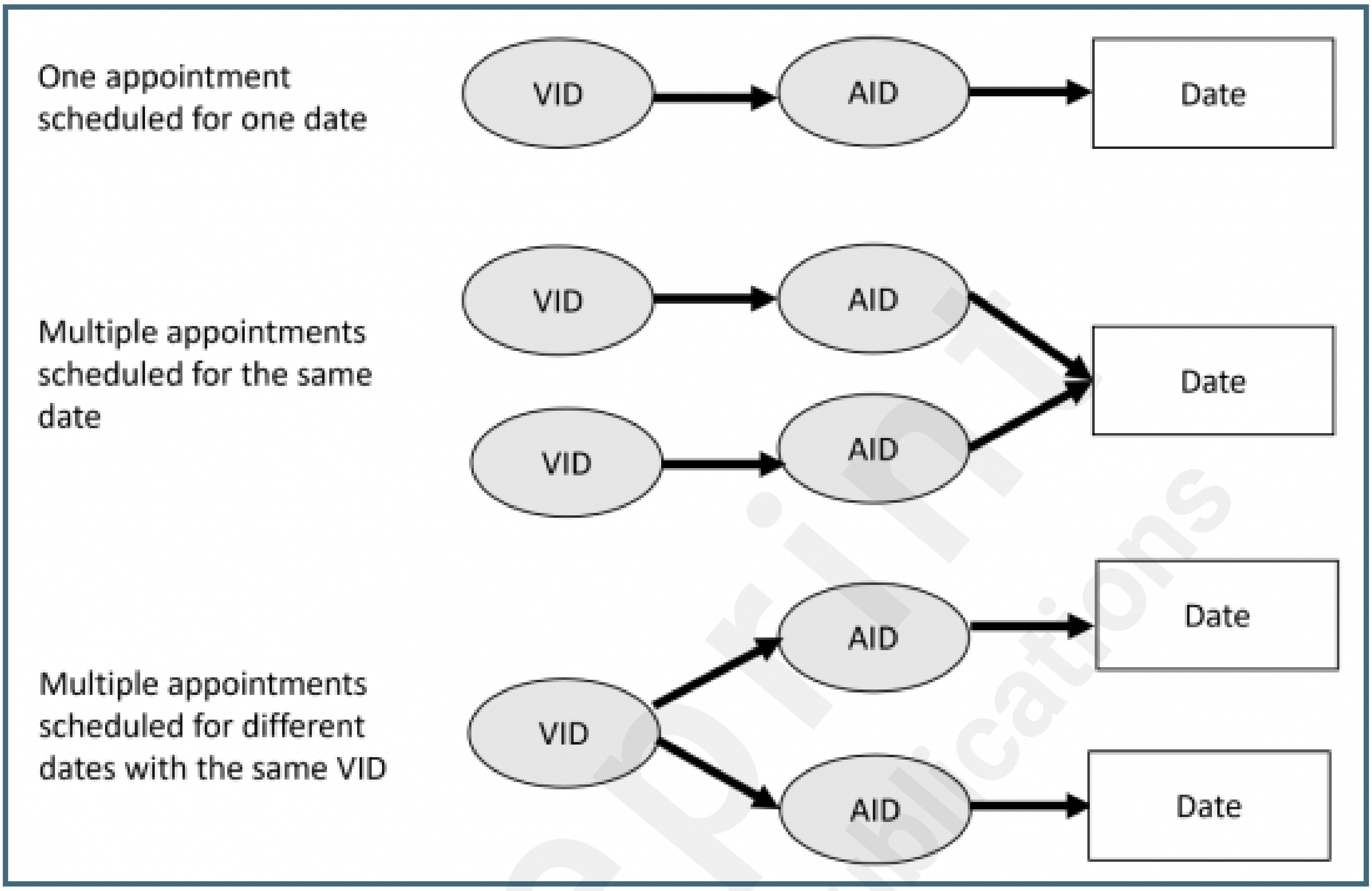
FIGURES

Figure 1: Illustration of appointment ID (AID) and visit ID (VID) possible scenarios
Figure 2: Four possible action outcomes for an appointment
Figure 3: Summary boxplots of arrived ratio, rescheduled ratio, canceled ratio, and no show ratio
Figure 4: Summary boxplots of sequence complexity, resolution complexity, location complexity, and scheduling complexity
Figure 5: Examples of high scheduling complexity and low count-based adjustments, high count-based adjustments and low scheduling complexity, low scheduling and low count-based complexities, and high scheduling and high count-based complexities

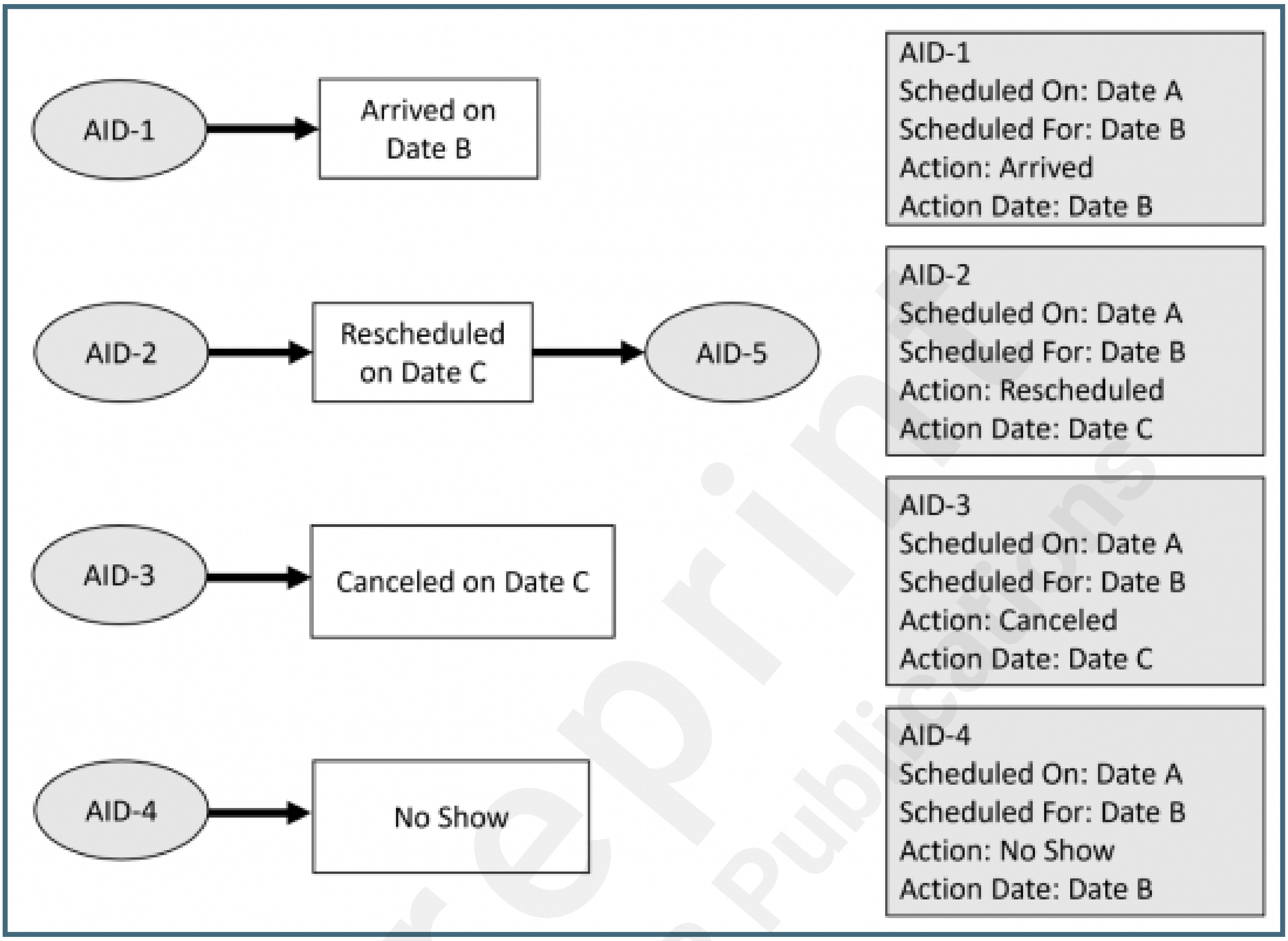
Supplementary Files

Figures

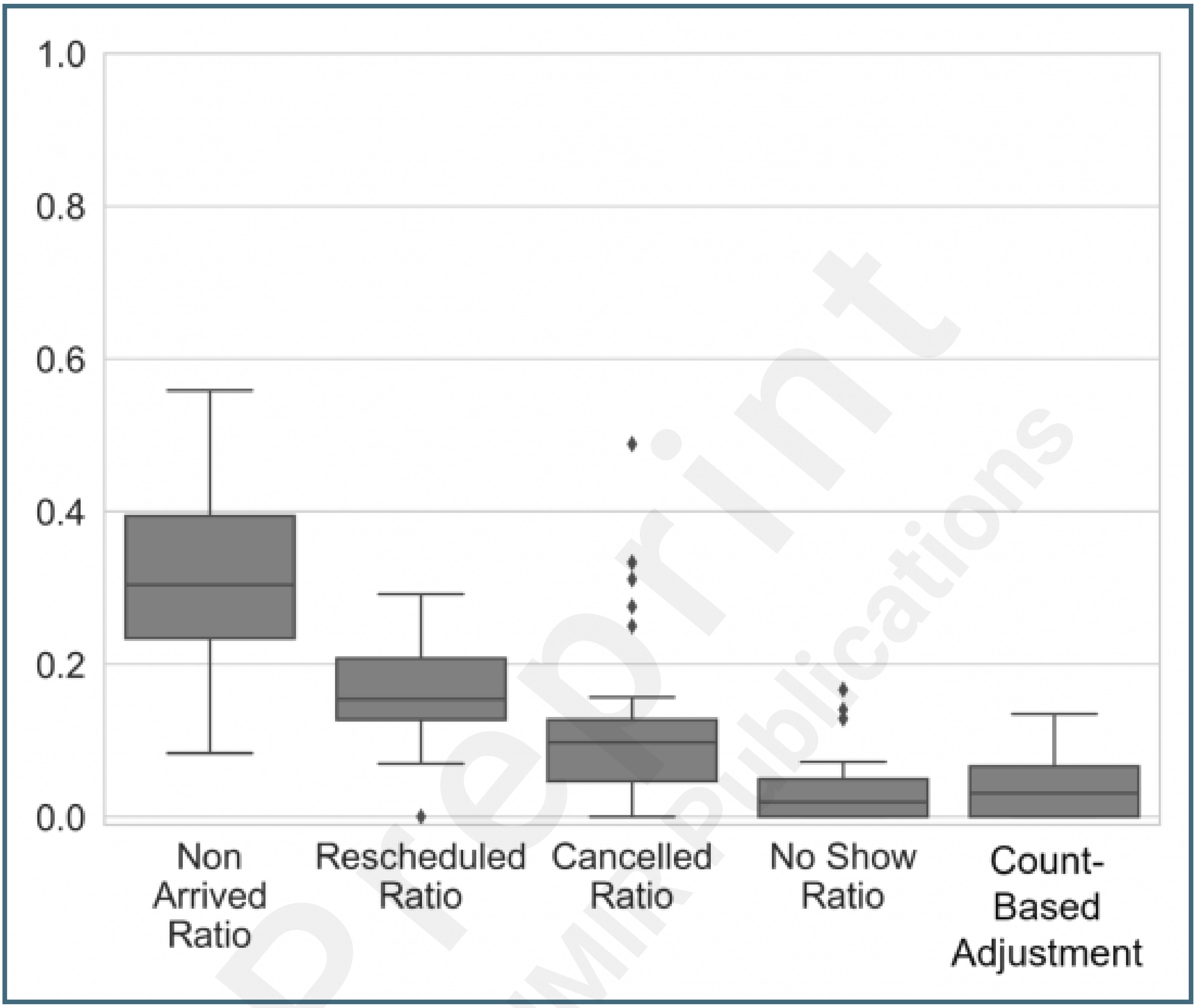
Illustration of appointment ID (AID) and visit ID (VID) possible scenarios.



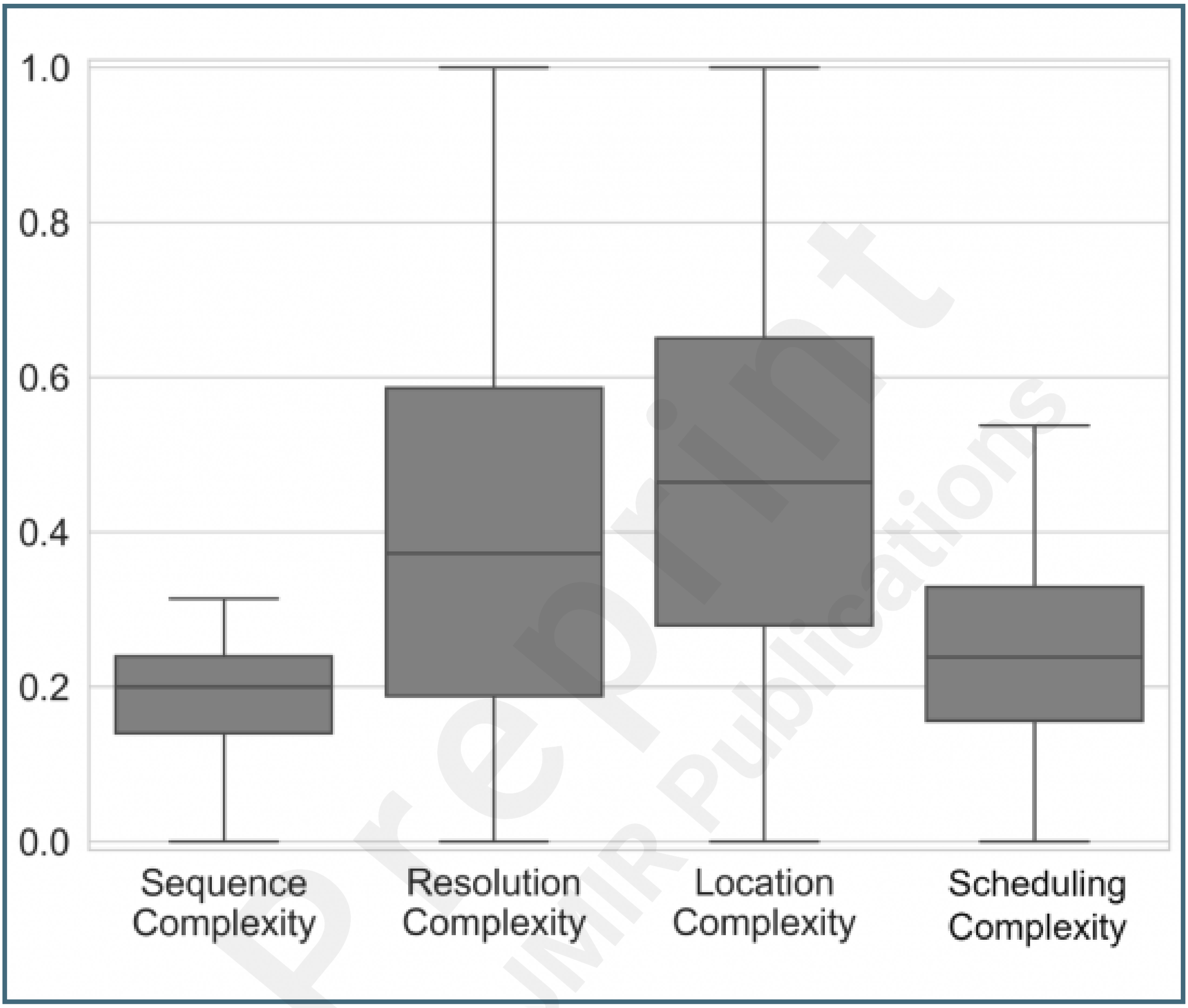
Four possible action outcomes for an appointment.



Summary boxplots of arrived ratio, rescheduled ratio, canceled ratio, and no show ratio.



Summary boxplots of sequence complexity, resolution complexity, location complexity, and scheduling complexity.



Examples of high scheduling complexity and low count-based adjustments, high count-based adjustments and low scheduling complexity, low scheduling and low count-based complexities, and high scheduling and high count-based complexities.

Patient A
Count-based adjustment: Low
Scheduling complexity: Low

VID	AID	Scheduled on	Scheduled for	Action	Action Date
1	1	8/7	9/9	Arrived	9/9
2	2	8/7	9/11	Arrived	9/11
3	3	9/9	9/17	Arrived	9/17
3	4	9/9	9/17	Arrived	9/17
4	5	9/9	9/30	Arrived	9/30
4	6	9/9	9/30	Arrived	9/30
5	7	9/21	10/13	Arrived	10/13
5	8	9/21	10/13	Arrived	10/13
6	9	10/2	10/23	Arrived	10/23
7	10	9/28	11/11	Arrived	11/11
8	11	11/9	12/18	Arrived	12/18
9	12	11/9	12/29	Arrived	12/29
10	13	1/4	1/8	Rescheduled	1/6
10	14	1/4	1/8	Rescheduled	1/6
10	15	1/4	1/8	Rescheduled	1/6
10	16	1/6	1/19	Arrived	1/19
10	17	1/6	1/19	Arrived	1/19
10	18	1/6	1/19	Arrived	1/19
11	19	1/9	1/20	Arrived	1/20
12	20	1/9	1/21	Arrived	1/21

Patient B
Count-based adjustment : High
Scheduling complexity: Low

VID	AID	Scheduled on	Scheduled for	Action	Action Date
1	1	2/6	3/16	Arrived	3/16
1	2	2/6	4/10	Arrived	4/10
2	3	3/17	4/14	Rescheduled	3/30
2	4	3/17	4/15	Rescheduled	3/30
2	5	3/17	4/16	Rescheduled	3/30
2	6	3/17	4/18	Rescheduled	3/30
2	7	3/17	4/19	Rescheduled	3/30
2	8	3/30	4/21	Arrived	4/21
2	9	3/30	4/22	Arrived	4/22
2	10	3/30	4/23	Arrived	4/23
2	11	3/30	4/24	Arrived	4/24
2	12	3/30	4/25	Arrived	4/25
3	13	6/9	9/10	Arrived	9/10
4	14	7/14	9/22	Rescheduled	9/21
4	15	7/14	9/22	Rescheduled	9/21
5	16	7/14	9/29	Rescheduled	9/21
4	17	9/21	9/24	Arrived	9/24
4	18	9/21	9/24	Arrived	9/24
5	19	9/21	10/2	Arrived	10/2
6	20	9/30	10/3	Arrived	10/3

Patient C
Count-based adjustment : Low
Scheduling complexity: High

VID	AID	Scheduled on	Scheduled for	Action	Action Date
1	1	5/20	5/21	Arrived	5/21
2	2	5/22	5/23	Rescheduled	5/22
2	3	5/22	6/2	Arrived	6/2
3	4	5/24	5/24	Arrived	5/24
4	5	5/21	5/28	Arrived	5/28
5	6	5/21	5/29	Arrived	5/29
6	7	5/21	5/31	Rescheduled	5/23
6	8	5/23	6/5	Arrived	6/5
7	9	6/4	6/4	Arrived	6/4
8	10	5/29	6/4	Rescheduled	6/2
8	11	6/2	6/7	Arrived	6/7
9	12	6/10	7/1	Arrived	7/1
10	13	6/7	7/26	Rescheduled	7/7
10	14	7/7	8/9	Arrived	8/9
11	15	6/21	7/29	Arrived	7/29
12	16	7/31	8/6	Arrived	8/6
13	17	7/1	8/7	Arrived	8/7
14	18	6/21	8/7	Rescheduled	7/20
14	19	7/20	8/10	Arrived	8/10
15	20	8/7	8/9	Arrived	8/9

Patient D
Count-based adjustment : High
Scheduling complexity: High

VID	AID	Scheduled on	Scheduled for	Action	Action Date
1	1	4/7	4/10	Arrived	4/10
2	2	4/2	4/25	Arrived	4/25
3	3	4/25	5/2	Rescheduled	4/30
3	4	4/30	5/1	Arrived	5/1
4	5	5/2	5/5	Arrived	5/5
-	6	4/28	5/5	Canceled	5/2
5	7	5/8	5/8	Arrived	5/8
6	8	4/29	5/11	Arrived	5/11
7	9	4/30	5/12	Rescheduled	5/5
7	10	5/5	5/20	Arrived	5/20
8	11	5/9	5/13	Arrived	5/13
-	12	5/8	5/17	No Show	5/17
-	13	5/8	5/18	Canceled	5/18
9	14	4/28	5/22	Rescheduled	5/12
9	15	4/28	5/22	Rescheduled	5/12
9	16	5/12	5/14	Arrived	5/14
9	17	5/12	5/14	Arrived	5/14
10	18	5/19	5/30	Arrived	5/30
11	19	5/10	6/1	Arrived	6/1
11	20	5/10	6/2	Arrived	6/2