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A Review of the Present State of Ambulatory Care Outpatient Oncology Workflows and the Clinical Value of Indoor Locating Systems

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Abstract

Pressures from high patient volumes, performing treatments once reserved for inpatient visits, and new financial programs drive departments to do more with existing resources. There is a significant body of knowledge about the challenges inherent in ambulatory care outpatient workflows setting up the need for developing, implementing, and using location-based technologies to help automate outpatient workflows on the day of service. We share the clinical value of indoor locating systems and give a simple example showing the efficacy of using location-based predictive analytics to improve the patient experience by properly managing resources and translate directly to better working conditions for the clinical staff. To make our point, we design, and model fit a simple, single predictor logistic regression model that could help reduce wait time and customize the patient experience by the staff actions to attend to the waiting patient.

Keywords: Ambulatory care outpatient workflows; Oncology services; Logistic regression model; Location based predictive analytics

Introduction (Broad-spectrum Growth in Outpatient Care)

Paradigm shift

Today, many outpatient (OP) clinics offer inpatient (IP) type services. Critically, Abrams et al. [1] found that patient preferences, treatment innovations, new patient-centric technologies, and financial incentives are some of the causes of the shift in offerings. Moreover, Abrams et al. [1] showed such factors resulted in a 17% increase in total hospital revenues by OP services over 20 years from 1995 to 2016. According to a study [2], in 2016, patients had 883.7 million physician office visits with an incidence rate of 277.9 per 100,000 persons. Finally, 54.5% of visits in 2016 were to primary care physicians.

Far-reaching consequences

The consequences of driving more patient volume to a facility not designed for the added use cases cause staff to do more with existing resources. For example, performing other, formerly IP treatment services in the clinic increases the demand for existing medical resources like providers, rooms, labs, devices, and imaging services. Therefore, amplified demand places more pressure on both the institution and care teams to squeeze more value from existing resources to meet quality and efficiency goals and to elevate the patient experience.

The national demand for outpatient oncology services

Such pattern shifts add to the problem's complexity in other specialty clinic settings like oncology. The current national trend, if the patient health conditions allow, is to treat cancer patients in an OP setting rather than admit them because same-day release bodes well for the patient's wellbeing. For example, in 2019, slightly more than 19,000 board-certified oncologists directly treated cancer patients; yet, in that same year, oncologists diagnosed 1.7 million new cancers from the four primary kinds, i.e., colon, breast, lung, and prostate [3].

State-level demand on ambulatory OP oncology services

In 2016 New York State had the fifth-highest cancer incident rate in the U.S. at 474.8 cases per 100,000 people [4]. Additionally, the current joint male and female incident rate of new cases of invasive malignant tumors per year is 442.6 per 100,000 people [5,6]. Consequently, the above city-wide incidence rate increases the present patient volume for each site and conflates the aggregate financial and operational risks exponentially over time for incorrect changes to workflows. Thus, there is a significant risk to both the institution and patient wellbeing if changes to the workflow do not meet the smallest standards of care and treatment.

Workflow

In any health care setting, the workflow is the set of physical and automated tasks executed by staff and patients within and across institutions, departments, and even homes [7]. Moreover, workflows stratify across several levels, e.g., one person, between people, between departments, and across organizations. Workflows have temporal properties like sequential, simultaneous, and random occurrences. Incorporating OP treatment-based workflows with exam-type services forces organizations to evaluate the relationship between both kinds of workflows. The aims are to engineer them as natural, mutually operational systems for clinical, operational, financial, and quality outcomes. The result of correctly designed workflows is a higher quality of care, simplified access to services, efficient processes, increased revenue, reduced wait times, happier staff, and better documentation.

Patient flow

Institutional: Patient flow includes pre-encounter scheduling and registration workflows, encounter-based workflows on the day of service, and post-encounter tasks. Generally, the three categories resolve to at least five interrelated stages of patient experience, to wit:

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1) before arrival (intake and scheduling), 2) day of visit (arrival, waiting, and encounters), 3) discharge, 4) follow-up visit scheduling, and 5) visit documentation [8].

Clinic: Patient flow in the clinic on the day of the visit is a pervasive daily challenge for any outpatient institution. The standard set of clinical systems used to manage the patient workflows is the scheduling, revenue management, imaging, and electronic health records (EHR) systems. Using such methods, patients get arrived and checked into their appointments, begin the waiting stage, get labs executed, and then go to the exam or the scheduled treatment. However, the workflows of an ambulatory care clinic are not sequential and often perform *departmental* workflows in any order based on several operational factors. Specially trained care coordinators or session assistants help manage the flow of patients based on functional criteria unique to each facility, physician team, and room allocation plan.

Departmental: Oncology clinics include various essential departmental services like labs, examinations for various cancer specialties (i.e., lymphoma, myeloma, solid tumor, etc.), diagnostic imaging, and treatments, e.g., chemotherapy, interventional radiology, etc. Furthermore, the staff responsible for coordinating the care among the various scheduled patient encounters during the visit, coordinate the use of departmental resources, e.g., patients, rooms and physicians, to manage the flow of patients through the clinic as a holistic effort to achieve efficiency. Often, the job of care coordinators is to understand the application of departmental resources and work with other coordinators in other departments so that any patient visit moves smoothly and seamlessly through the entire clinic. As an example, of this kind of intradepartmental resource management, below explains the exam workflow to manage available resources in that service department.

Exam resources management: During the exam workflows, the object for care coordination during the visit is to decide the next patient move into an open exam room. The essential patient-centric resources are the providers and the exam rooms that create immediate value for both the hospital and patients; thus, these items are imperative to manage correctly. Consequently, the mission of care coordinators is to manage these resources to ensure the doctor-patient interaction in an exam room.

Patient, provider, and room: Crucially, for exam services the determinants of resource management are 1) the patients, 2) providers, and 3) rooms. The EHR supplies a daily appointment report displaying patient demographics, appointment information, and arrival status. The next patient to place into a room must have arrived on time, and completed any pre-visit needs (e.g., labs, vitals). Next, care coordinators consider the physician and guess their next availability to see the patient. Finally, the staff determine (guesstimate) if one of the provider's exam rooms is available. Once all those parts align correctly, staff places the next patient in the exam room and record the room number and the time entered in the patient's health record.

Issues with Standard Technologies

Clinical technologies like EHRs present their own set of challenges that negatively affect the quality of care, prevent efficient resource use, and do more work for the staff. Accurately, a study [8] shows that EHRs present several workflow challenges shared with complementary technologies in ambulatory outpatient care. For example, the clinical staff does not want to log in to multiple systems separately. Hence, any other systems must smoothly supply relevant information into the primary clinical tool used to manage operations.

Additionally, user interfaces are not uniform between different technologies and designed poorly. For example, certain design flaws cause users to perform excessive keyboard manipulations to see needed information among the disparate systems. Similarly, excessive clicks create user stress and more process delays. Furthermore, nonstandard methods with design and functionality flaws cause user disruption when they must switch between different paths and screens to enter and retrieve information. Therefore, modern technologies additive to the standard set above generally results in higher clinical workload. Hence, such problems form barriers to adoptions showed as complaints, reluctant use, or abandonment by clinicians [9].

Indoor Positioning and Locating Technologies: Design and Engineering

Importantly, the best solutions integrate with the clinical systems that providers use to manage their clinics and care for their patients. Now, technologies like indoor locating systems can play a crucial role by supplying just in time location-based statuses along with the actual location of the patient directly in the EHR or other pertinent clinical communication systems like smartphones or nurse call systems. The underlying technologies available today use computer vision, radio frequency (RF) signals, infrared light (IR) transmissions, and sound to signal the location of a tagged object or person. All commercially available systems need the institution to install or configure sensor infrastructure. Computer vision systems do not require objects or people to don tags; however, these systems have trouble correctly finding multiple humans in a single area [10]. RF-based systems are fashionable but not as exact as IR for room and chair-level precision. Ultrasound is close to IR accuracy but susceptible to ambient noise sources. Also, white light sources like the sun and certain kinds of computer and TV monitors interfere with IR sensors, but focusing the detector can solve such issues.

Clinical value: Adjustable visibility of people and things

Koyuncu et al. [11] survey study is an excellent primer on the available technologies in this field. The best indoor location-aware systems (LAS) do several things well. First, LAS accurately detects the location of a tagged entity (e.g., person or asset) for the facilities use case and level of granularity (resolution). The clinical needs determine the exact amount of granularity, like room, chair, or area level visibility. Some use cases like a warm welcome concierge service only requires about a 2 meters resolution to bring the patient and concierge together, while chair level workflows like infusion services need accuracy between 0.6 and 0.9 m. Second, LAS process the raw location data and use static conditional rules to capture clinical milestones at critical moments and interactions between tagged objects. Third, they supply the correct location-based information to clinical software like EHRs so that staff can readily consume the information in the context of care. For example, showing the elapsed alone time of the patient in the exam room. This ability to give Location as a Service (LaaS) is essential in the complete adoption of this kind of ancillary technology.

Clinical value: Provider and room resource management

Recall that the determinants of resource management are: 1) the patients, 2) providers, and 3) rooms. Also, earlier, we stated that the object for care coordination during the visit is to decide the next patient move into an open exam room. A LAS can supply location-based information into the EHR, like accumulated waiting times, current location, occupied exam rooms, alone time in the room, and show who visited the patient in the exam room. The value of a LAS is in the information placed into the EHR used during provider and room management. A location-aware system (LAS) system gives exact room-level information (in use, dirty, available), the providers' real-time location in the department, and their actual time with roomed patients, and length each patient spends in their exam stage. Crucial, the LAS can help free up care coordinators by automating the manual HER patient room-in process, which logs the time and room number of the event in the patient's health record.

Clinical value: Data collection for time studies related to resource management

Both Xie et al. [12] and Santibáñez et al. [13] had to use manual processes and people to collect time-based information by intrusively shadowing people in an in-situ time study. To do this with no impact on the patient and simplify work for the researchers, the use of a specially designed mobile indoor locating system can automate the collection of data. For example, a portable system can collect data on key clinical processes like wait and lone times, staff intervals in the exam room, and distinct visit interaction events like vital complete and other staff interactions. The helpfulness is in the portability of wireless versions of such a system because of the ability for temporarily placement in a clinic with minimal effort.

Clinical value: Data mining and decision support

The facility must then use data science and database experts to understand the needs of the clinic and how to connect patients to the care they need. That entails connecting staff to their patients through forecasting needs and problems. The ability to perform predictive surveillance is crucial to better resource management [14]. Also, the data science team must have access to and understand the structure of the database to enable rigorous data mining. Thus, the vendor must give unfettered access plus supply a complete codebook describing all aspects of the LAS database. Data discovery will reveal correlations between location, patient, staff, and asset interactions through clinical workflow milestones. Additionally, the system must have other raw location data items, e.g., location name, time the person or object entered and exited the area, tag type, etc.

Related Theoretical Models: Network Theory, Contact Patterns, and Human Movement

Smartphones, health, travel, and GPS applications have given much-needed datasets on contact patterns and human mobility in social networks. However, the study of outpatient mobility networks using such tools still is an open field. Currently, in the field of clinical workflow automation and analytics, EHRs, LAS, smartphone-based way finding applications, and institutional databases (IDBs) can produce very precise and exact datasets for this use case. For patient and staff flows, the technical challenge is developing space-time simulations using the available contact network data. A work [15] used network theory and data from wearable sensors to create simulations of infectious diseases. Consequently, such techniques will help to understand OP workflows that could inform the development of computational methods used in the existing network datasets.

Importantly, a study [16] shows that providers spend between 20% and 50% of their time engaged in non-patient care tasks. However, the present state of indoor locating technology does offer a partial solution in that it can automate real-time workflows [17]. Today, combining LAS, scheduling systems and EHR data supplies a rich dataset uniquely suited to describe the connectome of people-oriented networks in the clinic. The joint datasets include appointment data, clinical processes, intervals, the people involved, and event triggers to automate workflows.

Predictive analytics

Predictive systems are a model of the probabilistic relationships between triggers of an event (predictors) and an outcome variable of interest [18]. Model building is a distinct process, and organizations that master this process gain excellent strategic advantages by solving nagging operational problems with machine learning techniques.

Strategic advantage: Data is vital to predictive analytics, but real advantages come from the applications that enable the business user to perfect business outcomes [19]. Moreover, the value of significant data assets is not in the asset but in the strategic plan to use the organization's ever-expanding data resources to help automate tasks and give real-time decision support. Advanced prediction analytics combines well known descriptive reporting techniques with linear algebra, probability, calculus, and a dash of computer science.

Machine learning method

The essential elements of the modeling process are understanding the business need, data preparation, discovery analysis, feature (predictor variable) choice, model training, testing, then validation. The clinical case determines the outcome required, i.e., clustering, classification, or regression. Whereas, the data preparation step refines and divides the data into proportionate sets for the next four stages. Now, feature choice finds each relevant independent variable and the degree to which each contributes to the expected outcomes. Finally, the training and testing stage perfect the parameters of the predictive model, which results in reaching the best predictive accuracy in the validation stage [20].

An Outpatient Location-based Predictive Analytics Model

Problem statement

Critically, a study [21] showed that patients spend about 89.4% waiting and 10.6% receiving services. Conversely, Santibanez, et al. [13] produced a 70% reduction in wait time by improving resource allocation without the use of a LAS. Strategically, the goal is to maximize the positive patient experience by resolving conditions that result in excessive exam wait durations. The proposed model in this section needs to correlate, via survey and evaluation, the quality of patient experiences to the collected exam wait durations captured by the LAS system.

Figure 1 is a frequency model showing the nature of the wait duration experienced by about 3600 patient accounts over a week. Such data is available from the LAS database and contained in the clinical process tables. The right skewed trait of the data is promising as most patients wait times are ≤ 30 minutes threshold. The mean is the red line and is 15.2 minutes, and the median is the blue line at 10 minutes. However, about 50% of patients (1,500) wait longer than 20 minutes before entering the exam room whereas ~11% (713) patients have wait times, x, between 30 and 80 minutes.

Hypothesis

A location-driven predictive analytics solution can help staff know about an operational problem that negatively affects the patient experience. Additionally, the tool should help staff watch and respond to evolving situations before excessive exam waiting times affect patient's

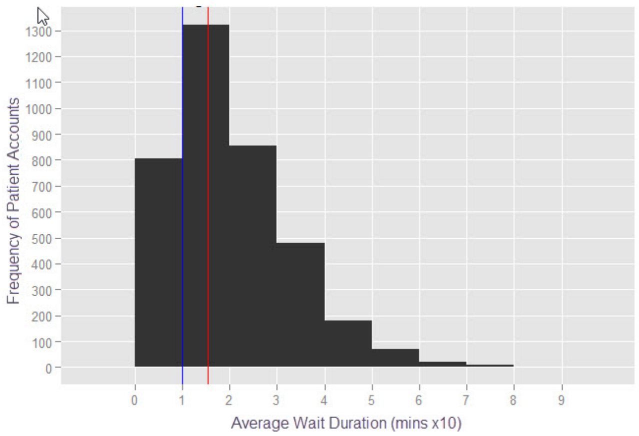

Figure 1: Example frequency graph of patient exam wait durations.

experience. Last, the data sources that to drive this predictive algorithm are homogeneous and exist in a single location-aware, context-aware locating system (LACAS) database. However, combining the LACAS data with data from other clinical information systems will give more context to the situation.

Therefore, the primary task is to create a real-time predictive analytics solution that supplies an in-situ, immediate visual notification to staff to manage the evolving problem customized to individual patients. Thus, a logistic regression model calculates the probability given the predictor Average Wait Time. The average wait is the duration in minutes from patient check-in to the moment the patient enters the exam room. Finally, the probability that the patient becomes frustrated and reports negative patient experience after completion of the exam given the average wait time is P (patient reports negative experience | Average Wait Time ≥30 minutes).

Deliverable

The project deliverables include one secure smartphone widget that displays a text message to staff pagers that displays a binary (yes/no) output when the logistic regression predicts the binary output (yes, or no) using average waiting duration as the input variable predictor. The algorithm chosen to model the issue is the sigmoid function with two coefficients. In the event the state changes to a yes condition, a rule will trigger and route the message to the proper staff group in the right department telling them which waiting area and patient cohort to help.

Data collection

First, Table 1 is an anonymized excerpt of exam wait durations from the full data set, which holds about 12,000 records for the period from August 2017 through October 2017. IR wearables, rather than RF, generate the location data and the LAS system stores it in a unique database.

The model fit

The tools used to carry out data extraction and initial explorations were SQL Server Management Studio (SSMS) and RStudio. SSMS helped to obtain the core data sets from the LAS database. In the R environment, we used the reshape2 and dplyr packages and the melt() and cast() functions to transform (i.e., shape) the data into the form and factors required for the model input. Additionally, use RStudio to fit the two unknown parameters, (Θ_0, Θ_1), to the model using only the training set's vector of average wait time as input. The R package used for logistic regression modeling and visualization was ggplot2. Finally, the generalized linear model, glm() with parameter family='binomial', processes the data.

The sigmoid function above (Figure 2) produces an S-curve (as modeled in Figure 3) with an output range where $0 \leq g(x) \leq 1$ for data with a Bernoulli distribution [21]. Model fitting the parameters (Θ_0, Θ_1) to the data, may show a curve as in Figure 3. Then, through expert advice and evaluation, choose a threshold value, e.g., the red line in Figure 3, along that scale to classify the output into one of two states $y \in \{0,1\}$. The illustrated threshold should define the point below which the decision to respond is no, and at that point is a yes. In this case, update the first hypothesis function and probability model to P (patient reports negative experience | Average Wait Time ≥ 60 minutes). Therefore, the goal is to produce a value near 0 for patients not expected to report a negative experience and 1 for those patients who will. Next, once the cost function output is at a local or global minimum, the prediction function, $g(x) \equiv pred(x)$, is ready for continuously updated vectors of values to drive the output. Moreover, based on the output value from the prediction function, staffs are engaged to help patients (Figure 3).

Process	Date	MRN	Tag	Room	MD	Time (Mins)
Waiting	10/16/17	123	1111	Rm 1	Hurts	21.8
Waiting	10/16/17	456	2222	Rm 2	Kildaire	39.8
Waiting	10/16/17	789	3333	Rm 3	Icursic	90.8
Note: All patient data has been de-identified. The Time (Mins) column is the length of the waiting duration from check in to the point the patient entered the exam room.						

Table 1: Extracted waiting process data from the indoor locating system clinical process.

$$g(x) = \frac{1}{1+e^{-x}}$$

Figure 2: Sigmoid function (Note: $x=\Theta_1^T X$, where Θ_1≡estimated parameter and X≡vector of average wait duration values from the indoor locating system's ClinicalProcess table).

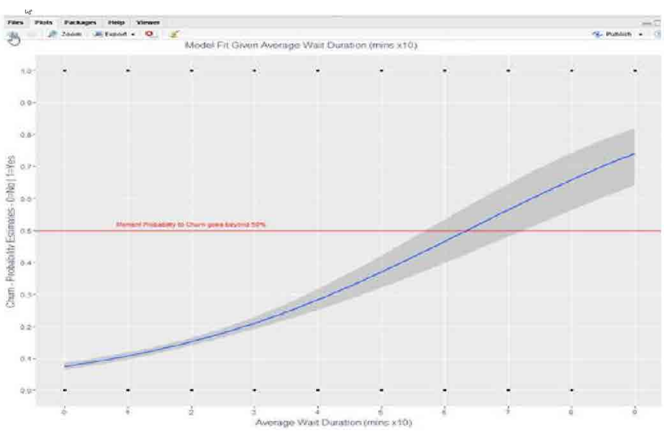

Figure 3: Example model fit given average exam wait durations (minutes x10).

Conclusion

Pressures from high patient volumes, performing treatments once reserved for inpatient visits, and new financial programs drive ambulatory care OP departments to do more with existing resources. An aging population, the incidence rate of chronic diseases, population growth, and a lack of trained physicians are some factors behind the change in underlying assumptions. We shared a significant body of knowledge about the challenges inherent in ambulatory care outpatient workflows to layout the need for developing, implementing, and using location-based technologies to help automate outpatient workflows on the day of service.

The clinical value of indoor locating systems is in the added real-time information about the clinical status of patients and colleagues. Data mining the LAS databases helps discover knowledge and information not readily available in other systems. Plus, correct location-based datasets are the way forward for using location-based predictive analytics to improve the patient experience. Conclusively, by managing resources, patients may have lower wait times. Also, better resource use may result in better working conditions for the clinical staff. Finally, the single predictor logistic regression model is one method to reduce patient wait time and customize the patient experience. By sending the team to attend to the patient who is experiencing long waits, the patient may feel more satisfied.

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