Predictive Analytics in Practice: A Novel Simulation Application for Addressing Patient Flow Challenges in Today's Emergency Departments

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Abstract

Objectives: To develop a flexible software application that uses predictive analytics to enable emergency department (ED) decision-makers in virtually any environment to predict the effects of operational interventions and enhance continual process improvement efforts. To demonstrate the ability of the application's core simulation model to recreate and predict site-specific patient flow in two very different EDs: a large academic center and a freestanding ED. To describe how the application was used by a freestanding ED medical director to match ED resources to patient demand.

Methods: The application was developed through a public-private partnership between University of Florida Health and Roundtable Analytics, Inc., supported by a National Science Foundation Small Business Technology Transfer (STTR) grant. The core simulation technology was designed to be quickly adaptable to any ED using data routinely collected by most electronic health record systems. To demonstrate model accuracy, Monte Carlo studies were performed to predict the effects of management interventions in two distinct ED settings. At one ED, the medical director conducted simulation studies to evaluate the sustainability of the current staffing strategy and inform his decision to implement specific interventions that better match ED resources to patient demand. After implementation of one intervention, the fidelity of the model's predictions was evaluated.

Results: A flexible, cloud-based software application enabling ED decision-makers to predict the effects of operational decisions was developed and deployed at two qualitatively distinct EDs. The application accurately recreated each ED's throughput and faithfully predicted the effects of specific management interventions. At one site, the application was used to identify when increasing arrivals will dictate that the current staffing strategy will be less effective than an alternative strategy. As actual arrivals approached this point, decision-makers used the application to simulate a variety different interventions; this directly informed their decision to implement a new strategy. The observed outcomes resulting from this intervention fell within the range of predictions from the model.

Conclusion: This application overcomes technical barriers that have made simulation modeling inaccessible to key decision-makers in emergency departments. Using this technology, ED managers with no programming experience can conduct customized simulation studies regardless of their ED's volume and complexity. In two very different case studies, the fidelity of the application was established and the application was shown to have a direct positive effect on patient flow. The effective use of simulation modeling promises to replace inefficient trial-and-error approaches and become a useful and accessible tool for healthcare managers challenged to make operational decisions in environments of increasingly scarce resources.

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Introduction

Background

In 1989, Charles Saunders, *et al.*, published a paper in *Annals of Emergency Medicine* entitled *Modeling Emergency Department Operations Using Advanced Computer Simulation Systems* [1]. In it, he presented a novel software application to quantify and predict patient flow in an emergency care setting. His model incorporated treatment spaces, providers, nurses, and even blood tests to demonstrate how the deployment of these resources drives emergency department (ED) efficiency. Dr. Saunders rightly concluded that the application of simulation-based tools had tremendous potential to improve ED operational performance. In fact, for decades, simulation tools and other systems-engineering techniques have been fully adopted by a wide variety of industries. Healthcare has lagged significantly in this effort.

Decades later, emergency department crowding is a rapidly growing problem affecting thousands of hospitals and millions of patients across the United States [2]. Long wait times are associated with a myriad of negative outcomes, including longer lengths of stay [1, 3–10], adverse clinical events [11–13], and decreased revenue [14–16]. As the demand for emergency care continues to rise [17], health systems are increasingly challenged to provide timely and cost-efficient care. However, despite advances in data and analytics since the work of [1], no readily available technology exists to enable EDs of all types to regularly benefit from systems engineering principles and simulation modeling.

The call to action to equip ED decision-makers with engineering tools and analytics is clear. The 2006 Institute of Medicine report, *Hospital-based emergency care: at the breaking point*, called for the application of systems engineering tools to improve patient flow [18], and there is a growing consensus that understanding the dynamics of ED care delivery demands an analytical approach [19]. The 2014 report of the President's Council of Advisors on Science and Technology, *Better Health Care at Lower Costs: Accelerating Improvement Through Systems Engineering*, recommended increasing technical assistance to help health systems adopt systems-engineering techniques [20]. Most recently, Janke *et al.* conclude that, "predictive analytics has the potential to improve the operational flexibility and throughput quality of ED services" [21]. In addition to the impact of ED crowding on patient care, the financial losses associated with crowding can easily reach millions of dollars annually for an ED [15], further justifying the need for new technologies that improve patient flow.

In recent years, these technologies have been applied to emergency care settings to forecast crowding [22–26], quantify the effects of patients who leave without being seen (LWBS) [27–31], assess triage and patient streaming mechanisms [4, 5, 32–34], optimize staffing [1, 35–39], examine the impact of reducing boarding times [33, 40], and analyze the financial consequences of crowding [14–16]. However, resources that provide this support in a single toolkit are not typically available to ED managers, and due to high technical barriers to entry, systems methods and tools remain broadly underutilized by decision-makers in emergency care settings [20, 41]. In particular, simulation modeling in the ED today is accomplished on a project basis; typically a research group, engineering and process support personnel, or external consultants use generic software that requires months of analysis and customization to simulate only a handful of operational scenarios. This approach has proven impractical for ongoing management and process improvement. The application described here represents a fundamental shift in how simulation can be leveraged by ED decision-makers. Namely, any ED decision-maker can design, execute, and analyze the results of a study simulating hundreds of operational scenarios within one hour, making simulation methods available for routine

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operations management and continual process improvement.

Importance

We describe a novel, scalable software application that enables ED decision-makers to routinely leverage systems engineering methods to manage their ED and improve performance. By leveraging easy-to-use interfaces, customizable simulation technology that can be adapted to any ED setting, and parallel cloud computing, this application enables decision-makers with no programming experience to quickly and accurately test the performance of operational changes in their ED without any clinical or financial risk. This information allows ED managers to make informed decisions that directly improve their patient flow.

Goals of This Investigation

The first goal of this investigation was to develop a scalable software application that can predict the effects of operational interventions in a variety of different ED settings. The second goal was to adapt the application to a large academic center and a freestanding ED to demonstrate its ability to accurately recreate and predict site-specific patient flow in two diverse ED settings. The third goal was to validate the ability of ED decision-makers to conduct simulation studies and incorporate the model's predictions in implementing operational changes.

Methods

The Application

Developed through a public-private partnership between University of Florida Health and Roundtable Analytics, Inc., supported by a National Science Foundation Small Business Technology Transfer (STTR) grant [42], the application integrates several key technologies, including: a web-based interface that enables users with no programming experience to design and launch simulation studies, a flexible simulation model that can be customized to any ED setting, on-demand cloud computational infrastructure that can rapidly simulate strategies within minutes, and a web-based interface that allows users to explore their results and identify top-performing strategies.

The core simulation code is written in R and utilizes stochastic, event-driven programming to model individual ED patient encounters. Adapted from Hurwitz, *et. al.* [33], this code incorporates: time- and acuity-dependent arrival rates, provider in triage and split-flow models, multiple levels of patient prioritization, multiple provider types such as physicians, residents, and advanced practice providers (APPs), a variety of labs and imaging, and variable boarding or discharge delays. Within the simulation model, the entirety of the ED patient experience is recreated: patients arrive, are triaged, placed in an available bed, receive care from nurses and providers, undergo lab tests and radiological imaging, are dispositioned and ultimately exit the ED after being boarded or experiencing a discharge delay. These processes have been modularized, that is, any ED can be simulated by appropriately coupling these processes in a manner that reflects actual ED workflows. The level of modeling detail enables specific "what if" questions to be asked of any particular ED-specific process to determine whether that component of the ED is a bottleneck of patient flow.

For customization to a new ED, the application requires only retrospective information that is already reported by the ED or captured within most electronic health record (EHR) systems.

Specifically, summary financials (e.g. hourly cost of different types of staff, collections, and payor mix) address all financial modeling requirements. Interviews of ED managers provide information regarding workflows, patient care processes and the ED's layout. Schedules of clinical personnel inform the staffing components of the simulation model. Finally, a retrospective data set is used to recreate the patient experience within the simulation model, from care delivery by simulated clinicians to the need for ancillary services such as labs and radiology imaging.

We note that both the features and usability of the software application result from more than 50 interviews of stakeholders representing EDs with widely varying patient volumes, workflows and geographies. A detailed description of the core simulation model is available in Appendix I.

Case Studies

We demonstrate the flexibility of the application by adapting it to two very different ED environments: a large academic center and a freestanding ED. By many metrics, most EDs fall somewhere between these two environments.

Academic Center

The first validation was performed at a 62-bed academic center in Gainesville, FL. Beginning August 3, 2015, decision-makers instituted a provider in triage between 9am-5pm on Monday, Tuesday, and Wednesday. To validate the core simulation model's ability to predict the effects of operational interventions in this ED, we selected two months of study: July-2015 (the last month without provider in triage) and August-2015 (the first month of provider in triage). We equipped the model with parameters that reflected July-2015 operations and conducted 100 one-week Monte Carlo simulations. We then compared the following model outputs to the actual observed outcomes from the academic center: LWBS rate (defined as the percentage of patients who left the ED before consulting a provider), median arrival-to-provider, median arrival-to-decision, and median arrival-to-departure. Next, we attempted to predict the outcomes from August-2015 by updating model parameters to reflect the addition of a provider in triage between 9am-5pm on Monday, Tuesday, and Wednesday. This process was consistent with how one would apply simulation modeling to prospectively make operational decisions. We then compared the actual observed August-2015 outcomes to those simulated from 100 Monte Carlo runs of the predictive model.

Freestanding ED

The second validation was performed at a 10-bed freestanding ED in Gainesville, FL, which opened in August, 2013. Between January 1, 2014 and January 1, 2015 the freestanding ED experienced an 84% increase in patient arrivals (Figure 1). Responding to this demand, decision-makers phased in secondary provider coverage.

To validate the core simulation model's ability to predict the effects of freestanding ED operational interventions, we selected two months of study: January-2014 (the last month without secondary provider coverage) and January-2015 (the first full month of secondary provider coverage). Similar to the academic model, we equipped the freestanding ED model with parameters that reflected January-2014 operations and conducted 100 Monte Carlo simulations. We then compared the model outputs to the actual observed outcomes from the freestanding ED. Next, we attempted to predict the outcomes from January-2015 by first updating model parameters to reflect increased arrivals and acuity, the addition of an 11am-11pm APP shift, increased nursing coverage, and reduced boarding times due to more efficient transportation to the main hospital. We then compared the actual observed January-2015 outcomes to those simulated from 100 Monte Carlo runs of the predictive model.

To evaluate the sustainability of the current staffing strategy, we steadily increased simulated arrivals in the January-2015 model to prospectively evaluate the operational and financial effectiveness of replacing the APP with a physician. We also considered a triple-coverage strategy that changed the APP shift to 9am-5pm and added a 12pm-12am physician shift (the APP operated as a provider in triage between 12pm-5pm). We then compared the three staffing regimes to identify a "tipping point" when it becomes more cost-effective to switch to a new staffing strategy.

In September, 2015, we deployed the application for on-going use by freestanding ED decision-makers. At the time the application was deployed, arrivals to the freestanding ED were approaching the previously identified tipping point, and management decided to increase provider staffing. The freestanding ED medical director identified several different schedules he was willing to implement in his ED. After designing and running a simulation study around these ideas, he identified a top-performing strategy that would also maintain high provider satisfaction. Beginning in October, 2015, this new staffing strategy was implemented. We evaluated the application's role in the medical director's decision-making process, and compared the model's predictions to observed outcomes in October, 2015 to determine the accuracy of the model.

Data Sources

This study was approved by the Institutional Review Board as exempt.

ED characteristics such as treatment areas, bed counts, and provider schedules were obtained from the Department of Emergency Medicine. Operational data from the electronic medical record (EMR) was provided by the University of Florida Integrated Data Repository (IDR) and the Office of the Chief Data Officer; financial data was obtained from the UF Health Faculty Practice Decision Support (FPDS) and the UF IDR. Model inputs were derived from these data.

Outcome measures including LWBS rate and arrival-to-event times were calculated from operational data provided by the UF IDR and used to validate each simulation model. A complete description of the data elements can be found in Appendix II.

Results

Development

Our collaborative development efforts resulted in a scalable software application that enables ED managers with no programming experience to use simulation modeling to inform operational decisions in their ED. The simulation model can be adapted to any ED setting, and after a brief, site-specific customization, the application can be ready for on-demand use by ED decision-makers. Importantly, once the model is parameterized, no protected health information is required by the application and no local installation of the application on hospital IT systems is necessary.

To begin a simulation study, ED decision-makers first access a web-based interface where they can quickly select a variety of operational changes to test. Within a few minutes, users can submit a batch of hundreds or thousands of different strategies without manipulating a single line of computer code.

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Once a study is submitted, the application leverages on-demand cloud computation to simulate strategies in parallel. In less than an hour, the simulation results are processed and summarized. Users access this information in a separate, web-based interface where they can filter, rank, and compare strategies based on outcomes such as LWBS, arrival-to-event times, or even financial metrics. This allows users to quickly identify top-performing strategies. An open, online demonstration of this process is available at http://solutions.roundtableanalytics.com/Emergency-Department-Simulation/.

Validation

Academic Center

When the model was equipped with parameters derived from July-2015 academic ED data, the simulated distributions of key outcomes were narrow (Table 1): The model-derived 95% prediction interval for LWBS rate was (8.29%, 11.38%); the intervals for median arrival-to-provider, -disposition, and -exit were (53 mins, 65 mins), (288 mins, 313 mins), and (410 mins, 439 mins), respectively. Moreover, the observed outcomes from the academic ED fell within the the model's prediction intervals: the observed LWBS rate was 9.14%, the observed median arrival-to-provider, -disposition, and -exit were 56 mins, 304 mins, and 430 mins, respectively.

Similarly, when the model was equipped with parameters to reflect August-2015, simulated distributions of key outcomes were also narrow (Table 1): The model-derived 95% prediction intervals for LWBS rate, median arrival-to-provider, -disposition, and -exit were (5.56%, 8.85%), (33 mins, 46 mins), (289 mins, 312 mins), (410 mins, 432 mins), respectively. These intervals again captured the observed metrics: the observed LWBS rate, arrival-to-provider, -disposition, and -exit were 6.85%, 42 mins, 297 mins, and 425 mins, respectively.

Freestanding ED

When the model was equipped with parameters derived from January-2014 freestanding ED data, the simulated distributions of key outcomes were narrow (Table 2): The model-derived 95% prediction interval for LWBS rate was (0%, 1.27%); the intervals for median arrival-to-provider, -disposition, and -exit were (14 mins, 18 mins), (94 mins, 110 mins), and (114 mins, 131 mins), respectively. Moreover, the observed outcomes from the freestanding ED fell within the the model's prediction intervals: the observed LWBS rate was 0.30%, the observed median arrival-to-provider, -disposition, and -exit were 14 mins, 105 mins, and 122 mins, respectively.

Similarly, when the model was equipped with parameters to reflect January-2015, simulated distributions of key outcomes were also narrow (Table 2): The model-derived 95% prediction intervals for LWBS rate, median arrival-to-provider, -disposition, and -exit were (0%, 1.35%), (17 mins, 26 mins), (95 mins, 113 mins), (119 mins, 140 mins), respectively. These intervals again captured the observed metrics: the observed LWBS rate, arrival-to-provider, -disposition, and -exit were 0.65%, 25 mins, 111 mins, and 132 mins, respectively.

When simulated arrivals grew beyond January-2015 levels, the model predicted increased crowding (Figure 2). Specifically, the model forecasted that the monthly LWBS rate would likely increase beyond 3% if arrivals surpassed 2,800 visits per month. At that point, ED capacity would've been unable to keep pace with demand.

We then simulated the operational and financial sustainability of three different staffing models as arrivals increased. Specifically, we considered the current APP secondary coverage model, as well

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as two alternative strategies: physician secondary coverage, or physician and APP triple coverage. The model predicted a consistently lower LWBS rate when physician and APP triple coverage was simulated versus the APP model (Figure 2, left). The difference in LWBS rates grew as volumes increased. As simulated demand surpassed 2,800 visits per month, the model predicted a tipping point when the physician and APP triple coverage model became more cost-effective than either of the secondary coverage models (Figure 2, right). Although physician and APP triple coverage is more costly, the volume of patients at the point of inflection – along with increased efficiency attributed to the physician and APP versus the APP or physician alone – resulted in increased revenue that offset the additional staffing costs.

The identification of this tipping point assisted freestanding ED decision-makers in prospectively determining when an intervention would be needed. As arrivals approached 2,800 patients per month, the freestanding ED medical director decided to increase provider staffing. Using the application (Figure 3), the medical director designed a simulation study to compare the effects of 17 different physician and APP triple coverage staffing strategies and 3 different arrival rates – a total of 51 scenarios. The staffing strategies differed based on the hours of day each provider was scheduled; the arrival rates differed based on total volume. Less than an hour after submitting the study, the medical director accessed the results (Figure 4) and identified two top-performing strategies that were similarly sustainable as arrivals increased. He selected the one that would result in higher provider satisfaction, and in October, 2015, this staffing strategy was implemented in the freestanding ED.

We compared data collected from the freestanding ED in October, 2015 to the model's predictions (Table 3). Once again, the observed outcomes fell within the narrow, model-predicted ranges: the model-derived 95% prediction intervals for LWBS, arrival-to-provider, -disposition, and -exit were (0%, 2.07%), (8 mins, 17 mins), (96 mins, 119 mins), and (118 mins, 139 mins), respectively; the observed LWBS rate, arrival-to-provider, -disposition, and -exit were 0.37%, 16 mins, 109 mins, and 129 mins, respectively.

Limitations

Several assumptions were made in constructing the simulation model. Namely, the model assumes that a patient's tolerance before leaving without or during treatment is a function of acuity and waiting time. The model also assumes that the ED is staffed to schedule every day – *i.e.* staff don't call-out. In addition, rather than simulate nursing care in discrete intervals, the model assumes that patients occupy a fraction of a nurses time (corresponding to their acuity's nurse-to-patient ratio) at all times while the patient occupies a bed. Finally, parameters for which there was no data – such as the median time to perform a physical exam, or the amount of time providers spend walking from one room to the next – were estimated by academic ED and freestanding ED providers.

Discussion

Many emergency departments struggle to provide timely and cost-efficient care, and effective operational interventions demand the support of predictive analytics. Healthcare, however, has not fully embraced this approach. While many other industries have applied analytical models to reduce waste and increase efficiency, high technical barriers prevent many ED decision-makers from utilizing simulation tools routinely. As a result, decision-makers seeking to improve ED performance

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are relegated to a trial-and-error approach that often results in costly and lengthy failures before a workable solution is found.

The application described here represents the opportunity for a fundamental shift in ED operational decision support. By removing the barrier to entry to simulation modeling for nearly any ED stakeholder, simulation modeling is finally available for continual, routine use; decision-makers can accurately experiment with site-specific operational interventions without any clinical or financial risk. Only the most effective strategies are then implemented in the ED, bypassing the need for trial and error.

Two case studies demonstrate the practicality of the application for real-world ED management and process improvement. After customizing the simulation code to two qualitatively distinct ED settings, the application was shown to accurately recreate site-specific ED throughput in both environments. Furthermore, the application was able to predict the effects of specific management decisions as well as prospectively identify when additional interventions were needed – and which would be most effective – to maintain efficient patient flow. When coupled with site-specific financial data, this allowed for accurate marginal cost-effectiveness planning that is critical to healthcare enterprises.

Further, it was demonstrated how this application can be used by ED managers to drive operational decisions. The application's web-based, point-and-click interfaces enabled decision-makers with no programming experience to conduct their own simulation studies and identify top-performing strategies. The speed of the application also enabled ED managers to continually reevaluate the deployment of their resources in near-realtime. At the freestanding ED, this allowed decision-makers to eliminate trial-and-error approaches and rapidly implement operational interventions to improve patient flow. As a result, the freestanding ED's performance has been consistently and remarkably strong, even as patient demand surged to almost double the facility's planned capacity.

By many metrics, most EDs fall somewhere between a modestly-sized freestanding ED and a high-volume, hospital-based academic ED. The application's ability to accurately model both environments demonstrates its scalability to a wide variety of EDs that struggle to manage patient flow.

An extensively validated core simulation model, cloud computation, and accessible user interfaces have resulted in a predictive analytics application with the potential for use in nearly any ED setting by any decision-maker. This technology promises to replace inefficient trial and error approaches, enabling healthcare managers to make effective operational decisions in environments of increasingly scarce resources.

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Appendix I

To understand patient flow through the academic center and freestanding ED, the authors conducted in depth interviews with healthcare providers regarding work processes and operational characteristics. As a result, the model incorporates multiple distinct ED treatment areas (triage, main area, fast-track, trauma/resuscitation, etc.) with rooms and hallway beds, multiple types of labs and imaging (complete blood count, basic metabolic panel, plain film, computerized tomography, etc.), and four different types of providers: nurses, advanced practice providers, residents, and attendings. These ED resources can be easily customized to any setting. For example, the freestanding ED does not have residents or geographically separate treatment areas, while the academic center has five treatment areas staffed by a distinct combination of attendings, residents, APPs, and nurses.

The simulation model also assumes the following patient flow structure: Upon arrival to the ED, patients are triaged and streamed according to their Emergency Severity Index (ESI) score [43]. The most acute patients are immediately triaged as ESI-1 and are taken directly to a trauma/resuscitation bed where their treatment preempts that of lower acuity patients currently being treated. A fraction of ESI-2 patients also bypass triage and go directly to a bed. All other patients receive an ESI score between 2 and 5 in triage and move to the waiting room until a bed becomes available. If there is a provider in triage, patients in the waiting room may have labs or images ordered, or be dispositioned to discharge after a brief exam. Patients in the waiting room are then selected for bed assignment based on acuity and time of arrival. Patients who stay too long in the waiting room (i.e. who are not placed in a bed before their tolerance for waiting) leave without being seen.

Patients who do not leave are assigned to a bed, and are briefly assessed by a nurse. A history is taken and a physical exam is then performed by a physician; the physician might subsequently order labs or radiological testing, perform procedures, or disposition the patient. Patients who have labs or images ordered occupy a bed and receive intermittent nursing attention until the results are ready and a physician returns to review them; the physician can then order more tests, perform procedures, or disposition the patient. Patients who are dispositioned to discharge exit the ED after a short delay to receive discharge instructions; patients dispositioned to admit remain in their assigned bed and receive care until a hospital bed is available – a process known as boarding. In the academic model, admitted patients are admitted to either an acute care unit, intermediate care unit, or intensive care unit; there is a different, time-dependent distribution of boarding times for each of these units.

This patient flow structure can also be customized to any ED setting. For example, the freestanding ED streams ESI-5 patients to a 4-chair fast-track staffed by providers who also cover the freestanding ED beds, while the academic center streams ESI-3, ESI-4, and ESI-5 patients to a separate 17-bed fast track staffed by dedicated APPs and attendings.

The distribution of provider-patient interaction times, lab and imaging turnaround times, disposition-to-exit delays, and other stochastic events was modeled using lognormal random variables. One notable exception to the lognormal framework was patient arrival rates, which were modeled using a non-homogenous (time-dependent) Poisson process [44].

While patient-provider interactions are modeled as discrete interactions, nursing care is modeled continuously: the model assumes that patients occupy a fraction of a nurses time (corresponding to their acuity's nurse-to-patient ratio) at all times while the patient occupies a bed.

The simulation code is written in a functionalized, modular structure. This enabled the authors to rapidly build models that can accurately recreate site-specific workflow processes. The result is a flexible, detailed simulation model that can be quickly adapted to any ED setting.

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Appendix II

The following information was used to parameterize and validate the simulation models. Note: the data required to derive these statistics is routinely collected and stored by EHRs.

Name	**Description**
Arrival volume	Average patient arrivals by hour and day of week
LWBS rate	Average percent of patients who LWBS per week
LDT rate	Average percent of patients who LDT per week
Time to complete registration	Median time from patient arrival to registered
Time to complete triage	Median time from triage start to triage complete
Time to complete nurse assessment	Median time for a nurse to take a history and vitals*
Time to complete provider assessment	Median time for a physician/resident/APP to conduct a physical exam and order tests*
Order rate	Percent of patients who had certain labs/images/procedures ordered†
Lab turnaround time	Median time from order to results†
Imaging turnaround time	Median time from order to read†
Procedure turnaround time	Median time from order to procedure complete†
Arrival-to-triage	Median time from patient arrival to begin triage assessment
Arrival-to-bed	Median time from patient arrival to placed in bed*
Arrival-to-provider	Median time from patient arrival to begin evaluation by physician/resident/APP*
Arrival-to-decision	Median time from patient arrival to clinical decision (admit, discharge, LWBS, etc.)*
Arrival-to-departure	Median time from patient arrival to exit from the ED*
Professional fee charges	Median total charges billed for professional services‡
Facility fee charges	Median total charges billed for facility services‡
Professional fee collections	Median total net collections for professional services‡
Facility fee collections	Median total net collections for facility services‡

**Grouped by ESI level*
†Grouped by specific lab/image/procedure
‡Grouped by evaluation and management code (or visit level) and payor class

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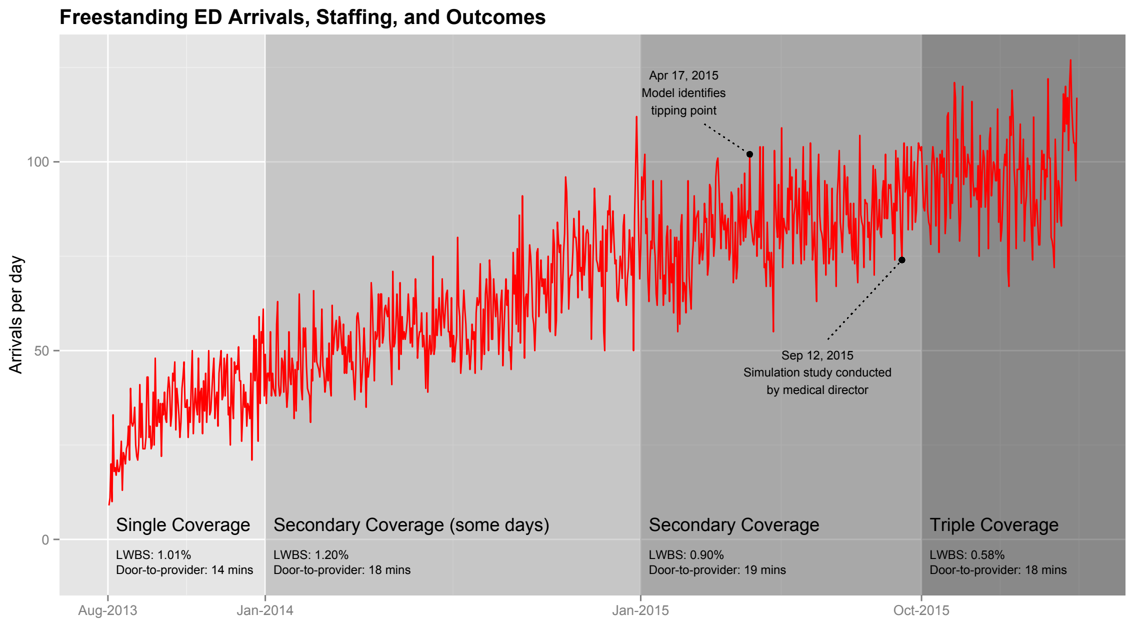

Figure 1: Freestanding ED Arrivals, Staffing, and Outcomes. Decision-makers have responded to growing demand by increasing staffing. As a result, the freestanding ED's performance has been consistently strong. *Arrival-to-provider reported as median over all patients treated in the timeframe.

Table 1: **Validating the Academic ED Model**

Outcome	July-2015		August-2015	
	Simulated*	Observed	Simulated*	Observed
LWBS rate (%)	(8.29, 11.38)	9.14	(5.56, 8.85)	6.85
Median arrival-to-provider (mins)	(53, 65)	56	(33, 46)	42
Median arrival-to-decision (mins)	(288, 313)	304	(289, 312)	297
Median arrival-to-departure (mins)	(410, 439)	430	(410, 432)	425

*Simulated values reported as 95% prediction intervals.

Table 2: **Validating the Freestanding ED Model**

Outcome	January-2014		January-2015	
	Simulated*	Observed	Simulated*	Observed
LWBS rate (%)	(0, 1.27)	0.30	(0, 1.35)	0.65
Median arrival-to-provider (mins)	(14, 18)	14	(17, 26)	25
Median arrival-to-decision (mins)	(94, 110)	105	(95, 113)	111
Median arrival-to-departure (mins)	(114, 131)	122	(119, 140)	132

*Simulated values reported as 95% prediction intervals.

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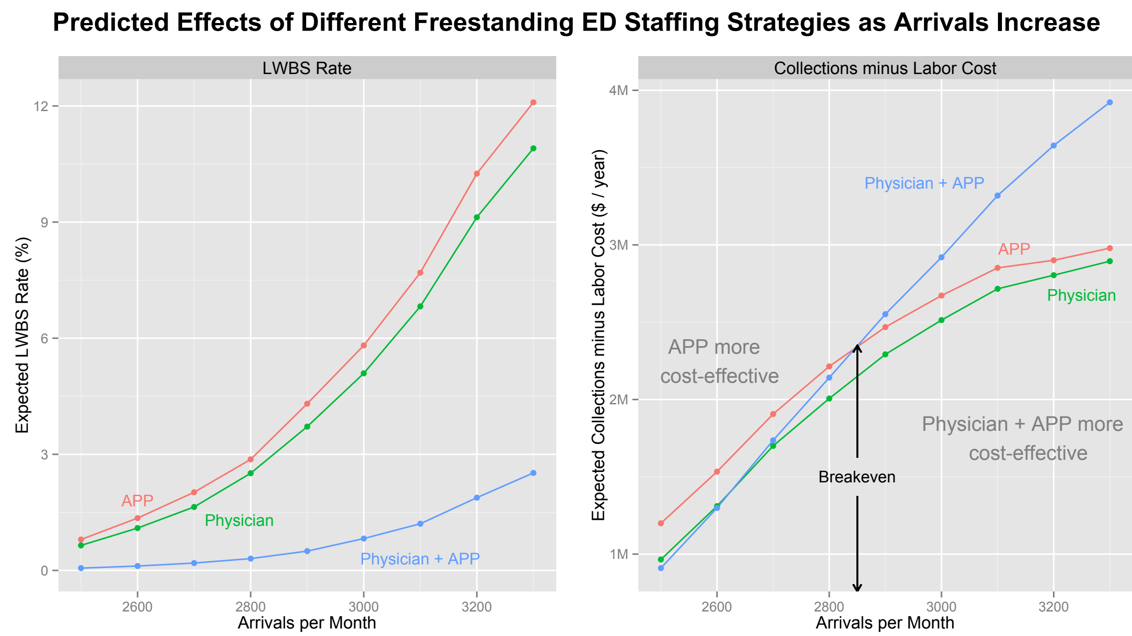


Figure 2: The simulated Physician + APP staffing model always outperforms the APP model with respect to LWBS rate. However, the added cost of triple coverage is not offset by increased throughput until arrivals surpass 2,800 per month.

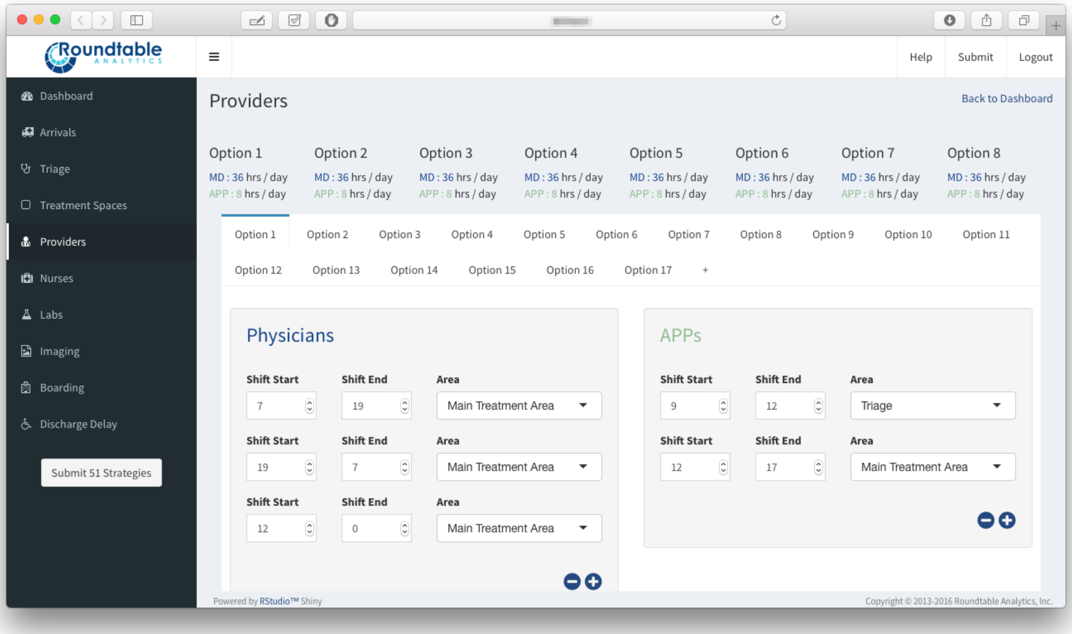
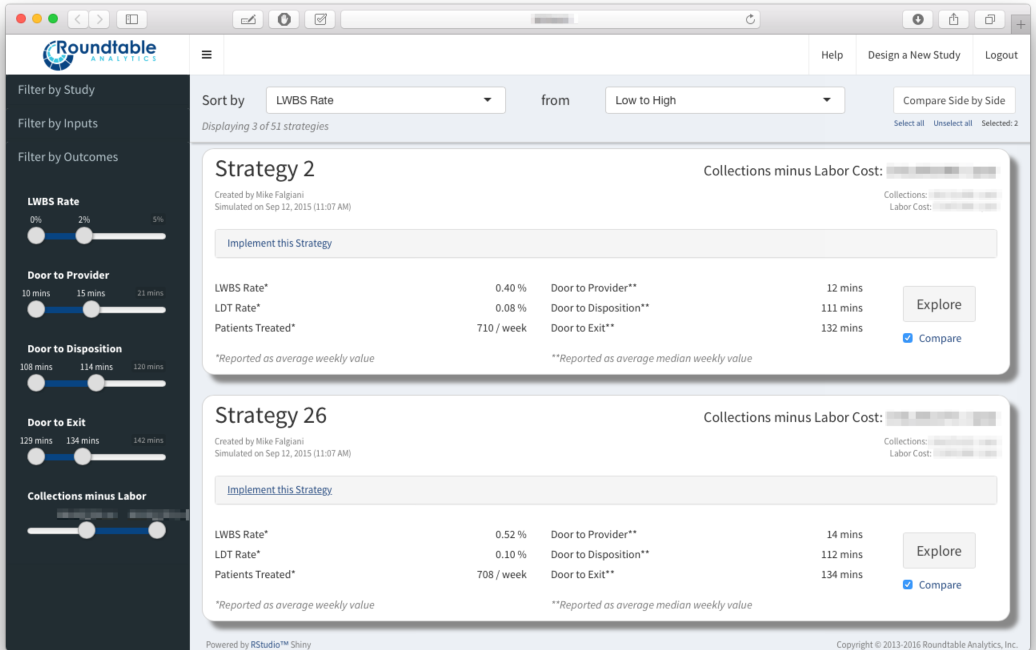


Figure 3: Screenshot of the freestanding ED study design interface. In this study, the freestanding ED medical director designed simulations to test how different provider staffing would perform under increasing arrivals.



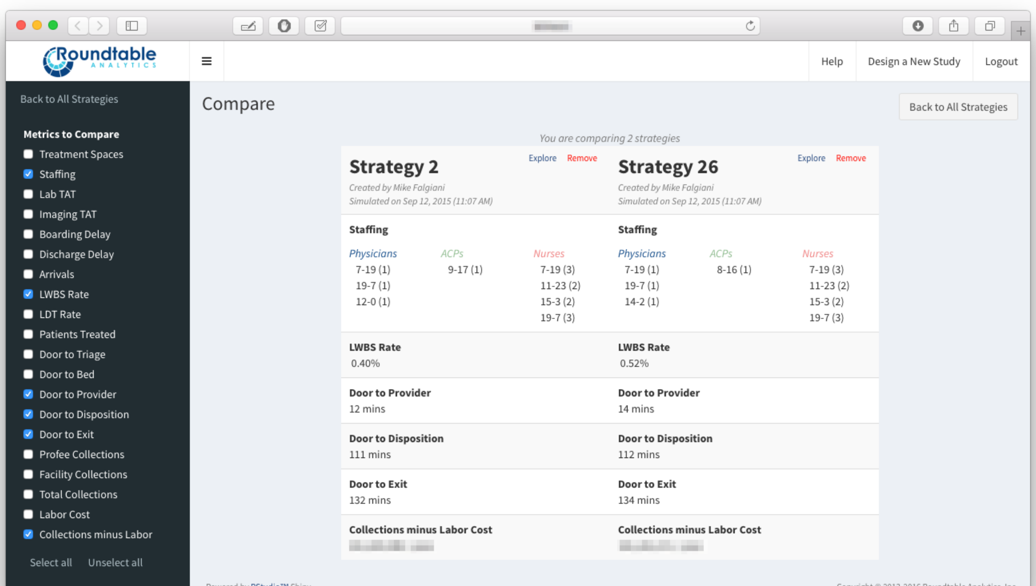


Figure 4: Screenshots of the freestanding ED results-interface. Less than an hour after submitting the simulation study, the freestanding ED medical director was able to filter and sort strategies (top) and compare top-performers (bottom).

Table 3: **Predicting the Effects of Staffing Changes in the Freestanding ED**

Outcome	October-2015	
	Simulated*	Observed
LWBS rate (%)	(0, 2.07)	0.37
Median arrival-to-provider (mins)	(8, 17)	16
Median arrival-to-decision (mins)	(96, 119)	109
Median arrival-to-departure (mins)	(118, 139)	129

*Simulated values reported as 95% prediction intervals.

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