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Study objective: We investigate the effect of admission process policies on patient flow in the emergency department (ED).

Methods: We surveyed an advisory panel group to determine approaches to admission process policies and classified them as admission decision is made by the team of providers (attending physicians, residents, physician extenders) (type 1) or attending physicians (type 2) on the admitting service, team of providers (type 3), or attending physicians (type 4) in the ED. We developed discrete-event simulation models of patient flow to evaluate the potential effect of the 4 basic policy types and 2 hybrid types, referred to as triage attending physician consultation and remote collaborative consultation on key performance measures.

Results: Compared with the current admission process policy (type 1), the alternatives were all effective in reducing the length of stay of admitted patients by 14% to 26%. In other words, patients may spend 1.4 to 2.5 hours fewer on average in the ED before being admitted to internal medicine under a new admission process policy. The improved flow of admitted patients decreased both the ED length of stay of discharged patients and the overall length of stay by up to 5% and 6.4%, respectively. These results are framed in context of teaching mission and physician experience.

Conclusion: An efficient admission process can reduce waiting times for both admitted and discharged ED patients. This study contributed to demonstrating the potential value of leveraging admission process policies and developing a framework for pursuing these policies. [Ann Emerg Med. 2014;64:335-342.]

Please see page 336 for the Editor’s Capsule Summary of this article.

INTRODUCTION

Background

Emergency department (ED) crowding has been recognized as a serious concern in US hospitals.1,2 Many studies have suggested potential solutions that modify arrivals, processes, and resources in the ED.3 Improved access to primary care and referrals can help nonurgent patients avoid ED visits.4-6 Separate care for minor injuries has contributed to reducing waiting times in the ED,7,8 whereas better staff scheduling and additional resources can also help increase throughput.9-13

More recently, studies have highlighted contributors to ED crowding that are typically viewed as being outside of the ED’s direct control, such as hospital bed shortages and boarding patients.3,12-14 Many hospitals have been making efforts to control hospital bed access and to change discharge policies of inpatient units to address high bed occupancy.15-17

Although the “back door” to the ED remains a challenge, less research has focused on the process of admitting patients in the ED and its effect on patient flow. An admission process involves both the ED and admitting services to begin the transition of a patient. A fragmented and inefficient admission process may cause delays in the transition and affect patient flows of not only admitted patients but also other ED patients.

Importance

The American Academy of Emergency Medicine encourages hospitals to develop policies that reduce the interval for completion of inpatient admission orders.18 However, a review of existing literature indicates that rigorous investigation of the admission process has been largely overlooked. We found only 2 relevant articles,19,20 but neither provided real insight into why the interventions were chosen. Several studies21-23 explored factors and processes associated with disposition decisions that emergency physicians made for ED patients. Although these decisions are related to admission processes with respect to the time and rate of admission order, the studies did not show how the decisions would affect patient flow in the ED. Our study overcame these limitations by extending the knowledge base...
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Table 1. Classification of admission process policies.

<table>
<thead>
<tr>
<th>Admitting Service</th>
<th>Emergency Medicine</th>
</tr>
</thead>
<tbody>
<tr>
<td>Physician group decisionmaking (attending, resident, intern, or physician extender)</td>
<td>Type 1: Decision by group of physicians on the admitting service</td>
</tr>
<tr>
<td>Attending physicians exclusively</td>
<td>Type 2: Decision by attending physicians on the admitting service</td>
</tr>
</tbody>
</table>

**Editor’s Capsule Summary**

**What is already known on this topic**

Patient flow in the emergency department (ED) is affected by formal and informal procedures.

**What question this study addressed**

The authors used discrete event simulation to estimate the effect of several different admissions processes for ED patients: processes varied by which service (ED or internal medicine) and which type of provider (resident or attending physician) was primarily responsible for the admission decision.

**What this study adds to our knowledge**

Compared with the baseline case (internal medicine resident team makes decision), alternative admission procedures could reduce length of stay for admitted patients by approximately 20% and that of discharged patients by approximately 5%.

**How this is relevant to clinical practice**

Small changes in procedure can yield important changes in flow; careful simulation studies can usefully inform these policy decisions before implementation.

about various admission processes. Using an advisory panel survey, we classified the admission process policies as a set of options and evaluated their potential effect by using computer simulation modeling. Simulation can provide decision support for operational and strategic planning to develop inpatient admission policies. Additionally, given the current emphasis on cost-effective solutions that improve patient flow, it is notable that changing the admission process policy does not require additional resources. However, as we will discuss, there are broader issues to consider before implementing changes.

**Goals of This Investigation**

Our study’s objective was to investigate various admission processes and their effects on patient flow in the ED. The goal was not to determine the most effective admission process for one hospital, but rather to provide a framework as a precursor to actual changes in policy. We used the term admission process policy to indicate a certain hospital protocol that determines admission processes for patients.

**MATERIALS AND METHODS**

As mentioned above, the literature on admission processes is limited. To better comprehend admission process policies, we surveyed an advisory panel group that consisted of 8 physicians in the ED and internal medicine at Hershey Medical Center. They each described the admission process of a hospital in which they had previously worked and assessed factors critical to quality for the process. We garnered 8 different admission process policies from the survey. Appendix E1 (available online at http://www.annemergmed.com) shows the survey form. All of the hospitals described are large teaching hospitals wherein the number of ED beds ranges from 20 to more than 100, with high patient volumes ranging from 40,000 to 100,000 annual ED visits.

Until now, many health care providers have designated 2 models for admission processes according to the department that makes a final decision: a consultation model and an emergency medicine decision model. However, the medical experience of the decision makers can also affect the efficiency of an admission process. Both the advisory group and a previous study indicated that an admission decision may be made more quickly and accurately when only attending physicians take responsibility for admitting patients than when residents or physician extenders are also involved in the process. Although attending physicians would make quicker decisions, there are fewer of them than residents or physician extenders. The effect of switching from a resident to an attending policy then becomes difficult to predict. Accordingly, this study classified admission process policies into 4 types, as shown in Table 1.

Types 1 and 2 are consultation models in which emergency physicians request consultations for potential admitting services and hand over admission decisions to the physicians on the admitting service. The final admission decision takes place when an admitting physician or physician group actually comes and examines a patient in the ED. This examination takes time; however, these types prevent patients from being transported to other units after they are admitted because the admission is determined by the admitting service physician. Types 1 and 2 also reduce the burdens of admission decision and procedures on emergency physicians so that they can attend to other ED patients. The difference between types 1 and 2 depends on how involved interns or residents are in the admission decision. In type 2, only attending physicians take responsibility for admitting patients and are therefore more efficient and accurate. However, this policy may deprive physician trainees of
the opportunity to learn appropriate decisionmaking for patients who need to be admitted to one of the inpatient wards.

On the other hand, types 3 and 4 are emergency medicine decision models that empower emergency physicians to determine admissions. The admission processes may be expedited because these types do not require waiting for consulting or an admission decision from an admitting service. However, these types can cause disagreement on the admission decision when a patient is admitted to an inpatient ward whose physicians think the patient belonged elsewhere. Similar to the difference between types 1 and 2, type 3 puts more emphasis on an educational value than type 4. Type 3 allows physician trainees to be the first to assess patients, which can increase their involvement in the decision to admit.

**Setting**

We conducted our study in a tertiary care, suburban, academic medical center in Pennsylvania with Level I trauma designation. The ED has 47 beds and an annual census of 64,363. To understand the current admission system of the hospital, the research team conducted a time-motion study and interviews with physicians, nurses, and a bed management manager. Figure 1 shows patient flow from the ED to an inpatient unit in the study hospital. This institutional review board–approved study used 1 year’s worth of data for 2012 from the hospital’s electronic medical record (FirstNet, Cerner, North Kansas City, MO). The data include the time stamps of every patient who visited in the ED, bed management data for inpatients, and staffing levels.

During 2012, 180 patients on average per day and 65,899 patients total visited the ED. Among the patients, this study focused on 52,428 adult patients. Figure 2 shows the distribution...
of patient arrivals in which the range of each hourly arrival rate was calculated during the course of the year. The ED arrival rates increased after 9 AM, peaked around 1 PM, and remained high until 10 PM. To reflect the variability of number of arrivals by times of a day, the simulation model used a nonhomogeneous Poisson distribution for arrival rates.

Emergency physicians requested a consultation of non–emergency physician services when a patient needed a special treatment or admission to the hospital. When a consultation was requested, a member of the admitting physician service came to the ED and determined admission after examining the patient. About 26% of the patients who visited the ED had at least 1 consultation order. Of the patients requiring consultation, about 21% had more than 1 consultation from different units; many trauma patients were in this category. Among 55 different admitting service units, the internal medicine service received the largest percentage by service, at approximately 28% of all consultations requested. Because of the larger volume of admitted patients, changes on the internal medicine admission process will have more influence on ED patient flow than changes on admission processes of other departments. For this reason, this study focused on investigating the admission process policies for internal medicine.

### Analysis

Currently, all levels of internal medicine physicians are involved in the admission process when emergency physicians request a consultation. That is, the hospital uses admission process policy type 1. To investigate the effect of changes in admission process policies, types 2, 3, and 4 were designed in simulation and compared with the current type. Two hybrid types of the 4 admission process policies were also considered to include other features of the system. Triage attending physician consultation is a hybrid of types 1 and 2, in which an internal medicine triage attending physician works primarily with the emergency physicians. The attending physician makes use of the ED tracking board to identify patients in the ED who are likely to be admitted to internal medicine and examines patients who need a consultation from internal medicine. After admitting a patient promptly, the triage attending physician assigns the patient to an internal medicine intern and works with the admitting intern to review the patient case. The second hybrid policy is a remote collaborative consultation in which both ED and admitting service attending physicians discuss a case remotely (by phone or computer) while viewing it through the electronic medical record. This admission process policy can be considered a combination of types 2 and 4.

This study aimed to explore how ED patient flow is affected by admission process policies. To do so, we could implement a new policy and compare the outcomes before and after the change. However, the demands of actually building the design and testing it are too high in terms of money, time, and risk. In particular, experimental risks are greater in hospital systems than other systems because unexpected results can affect patients’ safety. A computer simulation allows us to safely assess the issues that can be caused by the experimentation. The simulation approach provides other advantages too: it can represent a complex system, evaluate many scenarios, and predict results of alternative systems cheaper and quicker.25

We used discrete-event simulation, which has been widely used as a modeling and decision support tool in many health care areas.26 Discrete-event simulation is a particularly effective approach for investigating patient flow because it allows users to model various flows of individual entities and their interactions. In this study, individual patients, emergency physicians, ED nurses, and internal medicine physicians were modeled as entities or resources. Of the many discrete-event simulation software packages, we used Simio because it provides object-oriented design.

The baseline model represented patient flow under the current admission process policy (type 1), including all processes shown in Figure 1, from ED arrival to ED discharge to internal medicine discharge. In the simulation model, process times and other parameters were derived from the hospital data and time-motion study and expressed as theoretical statistical distributions to describe the stochastic properties of the patient flow. Goodness-of-fit tests validated the fitness of the distributions for hospital data. Appendix E2 (available online at http://www.anne emergmed.com) provides structural assumptions and key parameters of the simulation model.

We developed 5 additional simulation models that represent each admission process policy by modifying the baseline model with key assumptions. Although shifting the admission process policy from one type to the other could lead to many changes, this study concentrated on major and quantifiable changes for the simulation models. The first assumption was made for admission rates, depending on the locus of decisionmaking or the medical experience of decision makers. According to a pilot study, emergency physicians tended to be more conservative and admitted more borderline patients than internal medicine physicians. Also, for same ED patients, ED attending physicians were more likely than residents to admit a given patient, whereas internal medicine residents were more likely than internal medicine attending physicians to admit a given patient. We used the values from the study to determine the admission rate for each model.

The second assumption was made for the time to consult and the time for admission decision to order. In type 2, it was assumed that attending physicians make faster admission decisions and do not need to report to other physicians as interns and residents do in type 1. Because of the medical experience of admission decision makers, type 2 had reduced consulting times compared with type 1. On the other hand, types 3 and 4 omitted several processes from type 1, such as entering a consultation order and waiting for admitting physicians. However, for the 2 types, the time from admission decision to admission order still accrued. For type 3, it was assumed that residents and physician extenders report the admission decision to an ED attending physician for approval and enter the admission order. For type 4, the interval accounted only for entering and documenting the order, and therefore the process time was shorter than that in type 3.
The third assumption accounted for the number of available admission decision makers in each model. When all providers were involved in the admission process (types 1 and 3), any members in a team to which a patient was assigned could examine and admit the patient. However, when only attending physicians were involved (types 2 and 4), the number of available staff for the admission process was reduced. The effect of the reduced staff level was offset by the increased priority for patients waiting for an admission decision. That is, when only attending physicians were involved in the admission process, they prioritized seeing the patients who are likely to be admitted when the consultation order to admission order time and arrival to admission order time for patients who were discharged from the ED. Other time metrics were also included to measure how much the admission process policies affect other processes in the ED: arrival to consultation order, consultation order to admission order, arrival to admission order, and admission order to ED departure.

### RESULTS

We performed verification and validation of the simulation model to ensure accuracy and credibility of the model; Appendix E2 (available online at [http://www.annemergmed.com](http://www.annemergmed.com)) shows the procedures and results. Because it was confirmed that the baseline model closely represented patient flow in the hospital, we could conduct experiments with the system and predict system performance.

To identify the alternative admission process policies that differ significantly from the baseline, we used Dunnett’s test, a multiple comparison test. Table 3 shows the results of the 3 alternative models that include 95% confidence intervals (CIs) for mean difference and a percentage change in means from the baseline (Δ). A negative difference (Δ) indicates that the interval was shorter in an alternative model. The mean values were rounded to the nearest tenth, whereas the CIs were rounded to the nearest hundredth because of their narrow ranges.

The results showed that all admission process policy types significantly affected the admitted patient flow versus the current admission process policy. Type 2 reduced the consultation order to admission order time and arrival to admission order time by 66.1% and 24.7%, respectively, which led to the decrease of ED length of stay of admitted patients by 14.3%. Type 3 also reduced the consultation order time and arrival to admission order time by 66.1% and 24.7%, respectively, which led to the decrease of ED length of stay of admitted patients by 14.3%. Type 3 also reduced the arrival to admission order time by 33% and therefore reduced the ED length of stay of admitted patients by 19.8%. Among the alternative process types, type 4 had the most significant effect on the admitted patient flow: the arrival to

### Table 2. Main assumptions for alternative models.

<table>
<thead>
<tr>
<th>Assumption</th>
<th>Admission Rate, %</th>
<th>Time for Consult and Admission Decision to Order</th>
<th>Admission Decision Makers (Depending on Time of Day)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type 1</td>
<td>7.3</td>
<td>Triangular(20,40,60) * number of consults</td>
<td>2–4 providers in a team</td>
</tr>
<tr>
<td>Type 2</td>
<td>5.6</td>
<td>Triangular(20,40,60) * number of consults *0.5</td>
<td>1–4 attending physicians</td>
</tr>
<tr>
<td>Type 3</td>
<td>9.0</td>
<td>Uniform(10,20)*0.5</td>
<td>4–16 providers in a team</td>
</tr>
<tr>
<td>Type 4</td>
<td>9.2</td>
<td>Uniform(10,20)*0.5</td>
<td>1–4 attending physicians</td>
</tr>
<tr>
<td>Remote collaborative consultation</td>
<td>9.9</td>
<td>Triangular(20,40,60)*0.5</td>
<td>1 triage attending physician</td>
</tr>
</tbody>
</table>

### Table 3. Simulation model results for alternative admission process policies.

<table>
<thead>
<tr>
<th>Time Metrics</th>
<th>Baseline Model Type 1 (All IM Providers)</th>
<th>Type 2 (IM Attending Physicians)</th>
<th>Type 3 (All ED Providers)</th>
<th>Type 4 (ED Attending Physicians)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean, Hours</td>
<td>Mean, Hours</td>
<td>95% CI, Δ, %</td>
<td>Mean, Hours</td>
</tr>
<tr>
<td>IM admitted patients</td>
<td>A2CO</td>
<td>3.5</td>
<td>3.5</td>
<td>-0.03 to 0.01, -0.3</td>
</tr>
<tr>
<td></td>
<td>CO2AO</td>
<td>2.1</td>
<td>0.7</td>
<td>-1.44 to -1.40, -66.1</td>
</tr>
<tr>
<td></td>
<td>A2AO</td>
<td>5.6</td>
<td>4.2</td>
<td>-1.45 to -1.39, -24.7</td>
</tr>
<tr>
<td></td>
<td>A02D</td>
<td>3.8</td>
<td>3.8</td>
<td>-0.02 to 0.03, 0</td>
</tr>
<tr>
<td></td>
<td>ED LOS</td>
<td>9.4</td>
<td>8.0</td>
<td>-1.46 to -1.38, -14.3</td>
</tr>
<tr>
<td>Discharged patients</td>
<td>ED LOS</td>
<td>4.0</td>
<td>4.0</td>
<td>-0.01 to 0.01, 0</td>
</tr>
<tr>
<td>ED overall LOS</td>
<td>4.4</td>
<td>4.2</td>
<td>-0.18 to -0.16, -3.9</td>
<td>4.4</td>
</tr>
</tbody>
</table>

IM, Internal medicine; A2CO, arrival to consultation order; n/a, not applicable; CO2AO, consultation order to admission order; A2AO, arrival to admission order; A02D, admission order to ED departure; LOS, length of stay.
admission order time and the length of stay decreased by 35.6% and 21.4%, respectively.

On the other hand, the results indicated that the alternative admission process policy types had almost no effect on the discharged patient flow, except type 3, which increased ED length of stay of discharged patients by 1.2%. The global effect of the alternative types on the overall ED length of stay was a minor decrease, ranging from 0.6% to 3.9%. The limited effects on the discharged and overall patient flow were reasonable, considering the small proportion of patients admitted to internal medicine compared with the total number of discharged patients.

Because types 2 and 4 involve only attending physicians, they might be expected to have faster admission processing times than types 1 and 3. However, type 4 yielded results similar to those of type 3 on the arrival to admission order time and ED length of stay of admitted patients, perhaps because of the small number of available decision makers. Although attending physicians can examine and determine an admission order faster than interns and residents, the total number of available decision makers is reduced, which means patients may have to wait longer.

Table 4 shows the simulation results from 2 hybrid models, as well as comparisons of the results with those from the basic admission process policies. For Dunnett’s test, the control groups were set to the hybrid models, and treatment groups were set to basic admission process policies. The CIs and Δ correspond to the differences in means from basic admission process policies. A negative difference (Δ) indicates that the interval was shorter in a hybrid model. A triage attending physician consultation policy had a significant effect on both the admitted and discharged patient flow. Compared with that for types 1 and 2, the new policy led to decreased waiting times for admitted patients in the ED for all time metrics except the admission order to ED departure time, and as a result, the ED length of stay of admitted patients decreased by 26.4% and 13.3%, respectively. The smoother flow of admitted patients even reduced the average ED length of stay of discharged patients by about 5% compared with that for the 2 basic models. Among the admission process policies considered, the triage attending physician consultation policy had the most significant effect on reducing the overall ED length of stay: when the current admission process policy was shifted to the triage attending physician consultation policy, the overall patient flow was improved by 6.4%. Even though this efficiency was accomplished under given conditions in a simulation model, this result implies that the new admission process policy can cause a considerable change.

A remote collaborative consultation is a hybrid policy of types 2 and 4. When the admission process policy was changed from type 2 to this hybrid policy, the ED length of stay of admitted patients was reduced by 2.7%, whereas the overall length of stay slightly increased by 1.8%. On the other hand, the remote collaborative consultation policy did not make improvements to the same degree as type 4, possibly because type 4 was already very efficient compared with the current policy (type 1).

LIMITATIONS

The simulation study had several limitations. We made basic assumptions to build the alternative models, so the models did not represent all of the dynamic components observed in a hospital. Also, this study determined the parameters of the changes according to study results22 and physicians’ estimations because no data exist for the new models.

Because this study was conducted in an academic hospital, the effects of the admission process policies were framed in the context of teaching mission and physician experience. Therefore, the implications of the study results may be limited to academic medical center settings.

This study did not evaluate qualitative factors such as quality of care, patient satisfaction, and educational effectiveness. Although the simulation did not capture these important measures, we believe that efficient patient flow is closely associated with them.

DISCUSSION

We effectively used a simulation approach to model the complex patient flow and to estimate the combined consequences of various factors. The simulation models included patient attributes (eg, fluctuating arrival rates, acuity levels, and probability of admission), staff attributes (eg, different capacities during a day, process times, and responsibility for admission), and many different processes throughout the ED. Because the attributes were interrelated and the parameters were determined
by probability distributions, changes made in the model did not yield results in a linear fashion. For example, in types 2 and 4, the consulting process times were set 50% lower than those in types 1 and 3. However, consultation order to admission order or arrival to admission order were reduced less than 50% because of other associated factors such as admission rates and staff levels. The simulation results also indicated that eliminating the consultation process is not a simple solution for an efficient admission process. ED decision models (types 3 and 4) led to shorter ED length of stay of admitted patients compared with that for consultation models (types 1 and 2). However, type 2 had the most positive effect on the overall patient flow with respect to the average length of stay. This result may occur because emergency physicians were required to spend extra time for admission-related activities in types 3 and 4, and as a result, discharged patients waited longer for the physicians. The dynamic characteristics of the patient flow and the effect of admission process policies may be difficult to measure by observational studies or mathematical equations.

The simulation results suggested several important implications. The flow of internal medicine admitted patients strongly depended on the admission process policy: compared with the currently employed policy (type 1), their ED length of stay decreased by 14% to 21%. In other words, patients may spend 1.4 to 2 hours fewer on average in the ED before being admitted to internal medicine under a new admission process policy. This improvement is highly likely to affect patient satisfaction, staff workflow, and performance measures for evaluations. Although the actual effect of the modified admission process in a real clinical setting may be less than in a simulated setting, the simulation results still imply potential advantages that can be achieved by operational changes without using additional resources.

The overall influences the admission process policies had on all ED patients were relatively lower than the significant influences it had on the admitted patients. This result can be explained by the small proportion of the internal medicine admitted patients (approximately 5% to 10%) of the total ED population. The significant improvement in the small group may not drastically change the overall efficiency of a whole group. However, it is still meaningful that the 0.6% to 6.4% reductions in waiting times of all ED patients resulted from the modification of the current admission process policy applied for only 1 admitting unit. This result implies that extending the effort to modify admission processes of other admitting units could have a much greater effect on the overall ED patient flow.

Although all hospitals want to make processes more efficient, academic medical centers face the additional challenge of providing both clinical care and an educational environment for physician trainees. Numerous modifications to these basic admission process policy types can enable academic medical centers to meet their clinical and educational needs. For example, this study proposed and evaluated a triage attending physician consultation policy. In this system, an internal medicine triage attending physician uses the ED tracking board to identify patients who—by virtue of their emergency severity index, their age, and their presenting complaints and comorbidities—are likely to be admitted. This physician also examines patients who need consultations from internal medicine and determines admissions. The triage attending physician role was expected to significantly decrease the consultation order to admission order time. The simulation results confirmed this hypothesis in that better performance measures were observed under the triage attending physician consultation policy than in those for types 1 and 2. More important, this efficiency was accomplished without sacrificing the educational opportunity for internal medicine interns and residents to perform initial patient evaluations. Likewise, academic medical centers can balance the need for efficient processes with the needs of their physician learners by leveraging an appropriate admission process policy.

This study also investigated a remote collaborative consultation policy as a hybrid model of admission process policy types 2 and 4. The remote consultation has been used in various forms for years in close community practice. The emergency physician may telephone the admitting physician to discuss a case. After they reach an agreement, the nurse may take “verbal orders” for admission. This process is based on trust relationships built on physicians’ comfort with one another as individual decision makers and on the admitting physician’s personal knowledge of the patients and their needs. This personal knowledge of the decision makers or their lack of their experience is common in the academic or training world but may be less common in group practices. However, with the advent of the electronic medical record, remote collaborative consultation becomes a renewed possibility. The electronic medical record enables emergency physicians and admitting physicians to collaborate verbally while visualizing patient data in real time. Basing this joint decisionmaking on data helps prevent disagreements about the determination for disposition and reduces delays in the admission process by saving travel times to the ED for in-person evaluation. The simulation results showed that the remote collaborative consultation policy can make the admission process more efficient than when only internal medicine attending physicians are involved in the process (type 2). Though the remote collaborative consultation policy is efficient, it diminishes educational value. Accordingly, nonteaching hospitals may prefer this policy.

In summary, this study showed that hospital admission process policies from the ED to an inpatient ward affect both admitted and discharged ED patients. Through the classification of existing admission process policies and the analysis of simulation results, this study contributed to demonstrating the potential value of leveraging admission process policies and developing a framework for pursuing these policies.

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Emergency Medicine (DeFilich), Penn State Hershey Medical Center, and the Penn State University Center for Integrated Healthcare Delivery Systems (Kang, Nembhard, Rafferty, DeFilich), Pennsylvania State University, University Park, PA.

Author contributions: All authors conceived the study. HBN obtained research funding. CR and CD supervised the data collection. HK and HBN provided statistical advice on study design and analyzed the data. HK drafted the article, and all authors contributed substantially to its revision. HBN takes responsibility for the paper as a whole.

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REFERENCES


CORRECTION

In the August 2014 issue, regarding the article by Jesus et al (“Physician Orders for Life-Sustaining Treatment (POLST) and Emergency Medicine: Ethical Considerations, Legal Issues and Emerging Trends,” pages 140-144), this manuscript was developed by ACEP’s Ethics Committee pursuant to a committee objective assigned by the ACEP President. It has not been reviewed or endorsed by the ACEP Board of Directors.
APPENDIX E1.

Advisory panel survey form.

**Advisory Panel Input on Admission Processes from the ED**

The investigators are interested in analyzing the impact of admission processes from the Emergency Department to an inpatient department on the patient flow. We are asking the advisory panel to briefly describe the admission process carried out in a hospital in which you had previously worked (not HMC) using 4-6 steps.

**Name:**

**Title:**

**Email Address:**

**Name of Hospital:**

**Brief Description of Hospital:**
(E.g., 10 bed ED in a community hospital that serves 30,000 patients/year)

**Brief Description of Admission Process:**

- 
- 
- 
- 
- 

Assess the following critical to quality factors for the admission process used in the organization:

<table>
<thead>
<tr>
<th></th>
<th>Very Low</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
<th>Very High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Efficiency in the time from consult order to admission order</td>
<td></td>
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<td></td>
<td></td>
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<tr>
<td>Efficiency in the time from admission order to ED departure</td>
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<tr>
<td>Burden on ED physicians for admission</td>
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<tr>
<td>Burden on IM physicians for admission</td>
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<td>Input from IM service before admission</td>
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<td>Educational value gained through admissions for IM residents</td>
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<tr>
<td>Disagreement on the admission decision</td>
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</tbody>
</table>
APPENDIX E2.

Simulation model assumptions, verification and validation, and sensitivity analysis.

1. Structural assumptions and key parameters of the simulation model. Three structural assumptions underlay all of the simulation models. First, patients were continuously cared for by the same physician and nurses until they were discharged unless the assigned staff members were off shift. Second, no travel times accrued when patients and staff members moved between locations in the ED because those times were negligible compared with other process times. Third, no patients left the ED against medical advice after they were assigned to a bed until discharged.

The simulation models included all processes shown in Figure 1 from ED arrival to ED discharge to IM discharge. Patient flow and a series of procedures performed by care providers were mainly represented by process times, attribute assignments, and decision blocks. Additionally, the patient flow model also took into account other properties (such as staff schedules), using various functions of the simulation software. Because of space limitations, Table E1 summarizes only key parameters used in the baseline simulation model.

The data used in the simulation were obtained from 3 sources: time-motion study, hospital data, and expert opinions. Goodness-of-fit tests validated the fitness of the distributions for hospital data. Figure E1 shows examples of choosing the best-fitting distribution for the given data with @RISK software. Because data obtained from time-motion study and expert opinion did not include enough observations for estimating the fitted distributions, we used either a uniform distribution or a triangular distribution with the known mean values. The value after the last parameter in each distribution represents a specific random-number stream. For example, the Triangular(5,10,15,4) distribution will generate random numbers from 3 parameters (5,10,15) and a stream number (4). Process times are in minutes.

2. Verification and validation of the simulation model. Verification and validation of a simulation model is an important procedure to increase accuracy and credibility of the model. Verification was performed to ensure that the model was implemented correctly in the computer. We verified the model with the built-in “trace” and “animation” options in Simio.

Validation was carried out to confirm that the baseline model was an accurate representation of the study hospital. Physicians in the study hospital validated the model by reviewing the assumptions, parameter values, patient flow logic, and the structure of the system. Then, the results of the baseline simulation model were compared with the hospital data. Table E2 shows mean values and CIs. For IM LOS, ED LOS of discharged patients, and overall LOS, 95% CIs of the mean values of the simulation model included the mean values of the hospital data. Although mean values of other metrics tended to be higher in a simulation model, the differences from the hospital data were less than 8%. Because the baseline model closely represented behaviors of the patient flow in the hospital, we could conduct experiments with the system and predict system performance.

<table>
<thead>
<tr>
<th>Elements in the Simulation Model</th>
<th>Staff</th>
<th>Distributions</th>
<th>Data Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short registration time</td>
<td>Registration staff</td>
<td>Uniform(2,4,1)</td>
<td>TMS</td>
</tr>
<tr>
<td>Triage time</td>
<td>Triage nurses</td>
<td>Triangular(4.68,8.54,15,03,2)</td>
<td>HD</td>
</tr>
<tr>
<td>Acuity assignment</td>
<td>Triage nurses</td>
<td>Discrete(1,0.0054,2,0.1222,3,0.7918,4,0.991,5,1,3)</td>
<td>HD</td>
</tr>
<tr>
<td>Setup time for initial examination</td>
<td>ED nurses</td>
<td>Triangular(5,10,15,4)</td>
<td>TMS</td>
</tr>
<tr>
<td>Initial examination time</td>
<td>Emergency physicians</td>
<td>Triangular(5,15,30,5)</td>
<td>TMS</td>
</tr>
<tr>
<td>Laboratory testing/radiology needed?</td>
<td>n/a</td>
<td>Probability (0.8)</td>
<td>HD</td>
</tr>
<tr>
<td>Both radiology and laboratory testing needed?</td>
<td>n/a</td>
<td>Probability (0.59)</td>
<td>HD</td>
</tr>
<tr>
<td>Time from laboratory order to collection</td>
<td>ED nurses</td>
<td>Triangular(5,10,20,6)*2</td>
<td>HD</td>
</tr>
<tr>
<td>Time from radiology order to examination</td>
<td>Waiting time</td>
<td>Triangular(13,25,40,15)</td>
<td>HD</td>
</tr>
<tr>
<td>Time from laboratory collection/radiology examination to results</td>
<td>Waiting time</td>
<td>Min(300, Σ(1.1267,35.359,7))*2</td>
<td>HD</td>
</tr>
<tr>
<td>Laboratory results review time</td>
<td>Emergency physicians</td>
<td>Triangular(5,10,15,8)</td>
<td>EO</td>
</tr>
<tr>
<td>Consultation needed?</td>
<td>n/a</td>
<td>Probability (0.26)</td>
<td>HD</td>
</tr>
<tr>
<td>Consultation by IM?</td>
<td>n/a</td>
<td>Probability (0.28)</td>
<td>HD</td>
</tr>
<tr>
<td>Entering consultation order time</td>
<td>Emergency physicians</td>
<td>Uniform(5,10,29)</td>
<td>EO</td>
</tr>
<tr>
<td>Number of consulting assigned</td>
<td>IM physicians</td>
<td>Discrete(1,0.7,9,2,0.96,3,1,4,9)</td>
<td>HD</td>
</tr>
<tr>
<td>Time from consulting to admit order</td>
<td>IM physicians</td>
<td>Triangular(20,40,60,9)*</td>
<td>HD and NumbofConsulting</td>
</tr>
<tr>
<td>Admit to IM?</td>
<td>n/a</td>
<td>Probability (0.81)</td>
<td>HD</td>
</tr>
<tr>
<td>Consultation by other departments and admitted to IM?</td>
<td>n/a</td>
<td>Probability (0.07)</td>
<td>HD</td>
</tr>
<tr>
<td>Time from admission order to bed request</td>
<td>Waiting time</td>
<td>Min(197, lognormal(2.89,0.89,11))</td>
<td>HD</td>
</tr>
<tr>
<td>Time from bed request to bed assignment</td>
<td>Waiting time</td>
<td>Min(766, lognormal(3.98,1.21,12))</td>
<td>HD</td>
</tr>
<tr>
<td>Time from bed assignment to discharge order</td>
<td>Waiting time</td>
<td>Min(261, lognormal(3.99,0.62,13))</td>
<td>HD</td>
</tr>
<tr>
<td>Time from test results to discharge (necessary treatment time)</td>
<td>ED nurses and emergency physicians</td>
<td>Triangular(10,15,20,19)+Uniform(10,15,20)+30</td>
<td>HD and TMS</td>
</tr>
</tbody>
</table>

TMS, Time-motion study; HD, hospital data; EO, expert opinion; n/a, not applicable.
Figure E1. Examples of a goodness-of-fit test.
3. Sensitivity analysis. We performed a basic sensitivity analysis to show how the model reacts to input changes. For the analysis, we chose the IM admission rate and the time from consulting order to admission order among the many input variables. These 2 variables were the main assumptions that underlie development of alternative admission process policy types.

In the baseline model, the ratio of IM admitted patients to the total ED patients was 7.3%. With the result from a pilot study, the admission rates for the other 5 models were determined as ranging from 5.6% to 9.9%. Figure E2 shows how the change in the IM admission rate affects the LOS of 3 different patient categories. As the admission rate increased, the LOS of admitted patients increased but the incremental rate decreased. That is, when the admission rate was greater than 7%, the effect on the LOS remained almost constant. Overall LOS also slightly increased for the higher admission rate but did not have a significant effect.

Figure E3 shows the effect of the time from consulting order to admission order (CO2AO) has on the patient flows. In the baseline model, the CO2AO time was Triangular(20,40,60)*number of consulting. For alternative models, it was assumed that the CO2AO time reduced when IM attending physicians or emergency physicians admitted patients. The x axis represents the reduction rate for the current CO2AO time. For example, the first point of the x axis (0.2) is equivalent to the CO2AO time 0.2*Triangular(20,40,60)*number of consulting. As the CO2AO time increased, the LOS of admitted patients increased, but the other 2 LOS remained nearly unchanged. From the sensitivity analysis, we can draw 2 conclusions: (1) the CO2AO time had a more substantial influence on the flow of admitted patients than the admission rate; and (2) the simulation model was robust to the perturbations in the 2 assumptions from the possible minimum to maximum values.

APPENDIX E3.
Discrete-event simulation modeling procedures for the admission process

1. Input modeling

1.1. Collecting and cleaning data

This study obtained institutional review board–approved empirical data for a full year (2012) from the hospital’s electronic medical record. The data include the time stamps of every patient who visited the ED during the period, bed management data for inpatients, and staffing data. During the period, 65,899 patients total visited the ED. To improve the quality of the data, errors and inconsistencies were removed from the patient data. This study also focused on adult patients. As a result, 13,461 data entries were excluded from the analysis, and 52,428 patient data entries were used as input data for the simulation model.

1.2. Fitting probability distributions to input data

Discrete-event simulation can represent dynamic behaviors of a system that change by stochastic input variables. Using the patient flow data, we estimated the underlying probability distributions and parameters of events and implemented the transformed inputs in the simulation.

1.2.1. The arrival process

In many modeling cases of service systems, arrivals are assumed to follow a Poisson process in which events occur at the

Table E2. Validation of the base simulation model.

<table>
<thead>
<tr>
<th>Time Metrics</th>
<th>Hospital Data</th>
<th>Simulation Results</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean, Hours</td>
<td>Mean, Hours 95% CI</td>
</tr>
<tr>
<td>IM admitted patients, A2CO</td>
<td>3.5</td>
<td>3.48 - 3.49</td>
</tr>
<tr>
<td>(for patients)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>who were admitted to A2D</td>
<td>2.1</td>
<td>2.15 - 2.17</td>
</tr>
<tr>
<td>IM from the ED</td>
<td>3.7</td>
<td>3.76 - 3.78</td>
</tr>
<tr>
<td>ED LOS</td>
<td>9.3</td>
<td>9.39 - 9.42</td>
</tr>
<tr>
<td>IM LOS</td>
<td>140.9</td>
<td>141.2 - 141.6</td>
</tr>
<tr>
<td>Discharged patients, ED LOS</td>
<td>3.9</td>
<td>4.0 - 4.56</td>
</tr>
<tr>
<td>(for patients)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>who were discharged from the ED</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ED overall LOS</td>
<td>4.3</td>
<td>4.39 - 4.40</td>
</tr>
</tbody>
</table>

Figure E2. Sensitivity analysis for IM admission rates.

Figure E3. Sensitivity analysis for the CO2AO time.
rate of \( \lambda \) per unit time. Because of its assumption of independent arrivals, the Poisson process is a good approximation of unscheduled arrivals.\(^5\) As shown in Figure 2, however, ED patient arrival rates vary over the time of day, so a nonstationary Poisson process (NSPP) is more appropriate for modeling than an ordinary Poisson process to accommodate the time dependency.

To apply an NSPP, modelers must identify the intensity function (arrival rate function) \( \lambda(t) \) or cumulative intensity function \( \Lambda(t) \) over time \( t \). However, finding the appropriate form is difficult.\(^4\)\(^5\) Many studies have proposed estimation techniques for the parameters of an NSPP. They include nonparametric methods such as piecewise-constant estimation\(^4\) and piecewise-linear cumulative intensity estimation.\(^6\) Parametric modeling approaches were also introduced, such as the exponential-polynomial-trigonometric rate function\(^7\) and the piecewise-linear approximation.\(^8\) The estimated parameters form the basis for generating random variates.

Among various random-number-generating techniques, 2 have been widely adopted for an NSPP: an inversion transform method that uses a cumulative intensity function, and a thinning method that uses a maximum intensity function to determine the acceptance of generated samples. However, most modelers who use simulation software packages do not need to perform the procedures. Simulation software including the logic in a programming library generates random numbers for a certain probability distribution based on parameters defined by users.

For 2 reasons, this study chose a nonparametric piecewise-constant estimation that assumes the arrival rate as being constant over blocks of time. First, an accurate estimation of the arrival process may directly affect studies investigating the optimal capacity or schedule of resources to handle demands such as in call centers. However, the precise estimation of ED arrivals does not significantly affect the admission process, although it is associated with the overall patient flow in the ED. The second reason is due to the limitation of the software used in this study. Simio can accept only numbers as the parameters of an NSPP while providing the flexibility to choose intervals. Despite its simplicity, the method yielded a valid approximation of patient arrivals.

The interval \( (0, S] \) can be divided into \( k \) subintervals \( (a_0, a_1], (a_1, a_2], ..., (a_{k-1}, a_k] \), where \( a_0 = 0 \) and \( a_k = S \). Let \( C_i \) be the number of arrivals that occurred during the \( i \)th interval on the \( j \)th realization of the observation. The approximated arrival rate during \( i \)th interval is then the average number of arrivals over the \( n \) realizations, normalized for the length of the interval.

\[
\hat{\lambda}(t) = \frac{\sum_{j=1}^{n} C_i}{n(a_i - a_{i-1})}, \quad a_{i-1} < t \leq a_i
\]

for \( i=1, ..., k \). This study divided a day \( (0, 24] \) into 24 equal intervals of length and estimated the constant for the intervals during 365 days of observation.

1.2.2. Other input probability distributions

Besides arrival events, a discrete-event simulation includes other random inputs such as initial triage times by nurses, examination times by emergency physicians, and consultation times by admitting physicians. Probability distribution functions and parameters can be determined by hypothesizing distribution families with histograms and box plots and by testing their fitness. However, performing the statistical procedures for each input requires a significant amount of time and effort. @RISK software addresses problems by automatically finding probability functions that fit to the raw data. The software also lists the selected distributions in the order of goodness-of-fit test results. This study used the best-fitting distribution that passed the Kolmogorov-Smirnov test at \( \alpha = 0.05 \) and had the minimum square error. If no distribution was available, an empirical distribution was used in the model.

1.3. Common random numbers

This study used the simulation technique referred to as common random numbers, also called correlated sampling, to predict changes in the performance of alternative systems with comparison to the current system. In the modeling procedure, an appropriate use of common random numbers provides a more accurate estimation of the differences between systems. The common random numbers technique in the discrete-event simulation means that the same stream parameter is used in each of the simulated systems. This method enables the systems to generate the same sequence of random numbers, which contributes to reducing variability in estimated performance measures between scenarios. It is a good modeling practice to assign a dedicated stream for each input in a model and to use the same streams for alternative systems. The steam dedication maintains synchronization across different systems.\(^3\)\(^4\)

2. Output analysis

2.1. Replications

Simulation outputs have a stochastic nature because input data include random variables. To obtain more concrete results from the random output values, simulation models should be run more than once. The replication of a simulation model also helps perform statistical analysis because outputs in different replications are independently and identically distributed. The decision on the number of replications depends on the desired accuracy of results and amount of times allowed. A larger number of replications can increase the precision of estimators (to a certain point), but it also requires longer running times. This study ran each model with 30 replications. This setting provides a fair range of the CI.

2.2. Steady-state simulation

EDs run 24 hours daily (steady-state system), and setting initial conditions can be addressed in several ways to avoid bias.
An intelligent initialization includes finding the initial condition similar to a long-run state through data collection or a simplified mathematical model. On the other hand, a long running length of a model can reduce the effect of initial conditions on performance measures.

This study used a warm-up period to deal with the initial condition of the model. Because response variables are not collected during the specified warm-up period, we can assume that a system starts at a state where the warm-up period ends. To identify the length of a warm-up period, the approximate time for an empty system to become a busy state was calculated. In this study, a nearly stabilized system is equivalent to the hospital in which the ED and IM beds are filled. Using animation functions and statistical tools, the warm-up period was set up for 15 days, long enough to be representative of steady-state behavior.

**APPENDIX E4.**

**Main steps of the simulation model with Simio.**

Figure E4 shows a screenshot of the simulation model with the Simio software. Because of the space limitation, the image includes only patient flow from a consultation order to an admission order. The entire simulation models patient flow from ED arrival to ED discharge to IM discharge, which includes all processes shown in Figure 1. The figure is followed by descriptions on steps 1 to 10 and their properties. Many different functions of the simulation software were used to validate the model and obtain performance measures.

1. Decide whether a patient requires a consultation from IM

   Among patients who requested a consultation from an inpatient unit, approximately 20% had a consultation from IM. An entity (patient) is sent to a true path with probability 0.2 or sent to a false path with probability 0.8.

2. Assign a time stamp when a consultation order was entered

   Timenow is a built-in function that returns the current simulation time. The event time when an emergency physician enters a consultation order is assigned to an entity. This type of assigned value is used to calculate intervals between events.

![Figure E4. A screenshot of the simulation model with the Simio software.](image)
3. Assign an interval between an ED arrival and a consultation order

ModelEntity.TimeCreated is a built-in function that returns the simulation time when this entity was first created. With the assigned value, the time from ED arrival to a consultation order is assigned to an entity.

4. Update the tally statistic for the interval between an ED arrival and a consultation order

In the previous step, a value ModelEntity.ArrivalToConsultorder was assigned to an entity. This tally step adds the value of an entity to the tally statistic called ArrivalToConsultOrder.

5. Seize an IM physician for consultation on admission

An entity seizes an IM physician from candidate physicians included in the list (List_consultTeam). This study modified the list and a physician-selection rule for each of admission process policies.

6. Assign waiting times for the IM physician

The assign step records the waiting time for the IM physician who is requested by an entity. The waiting time is calculated from the time a consultation order was entered to the time the requested physician comes to the ED.

7. Update the tally statistic for the waiting time for IM physicians

The tally step adds the waiting time for the IM physician to a tally statistic.

8. Assign the identification (ID) of the seized IM physician

The ID of the seized IM physician is assigned to an entity. This information is required to release the physician after examining the patient and deciding an admission. The ID can be also used to keep track of physicians who made an admission decision.

9. Examine a patient

The seized IM physician examines the patient and makes a decision on an admission for the delay time, which follows the probability distribution function. This empirical distribution function was obtained according to the hospital data. Because a single probability function does not fit to the existing data, multiple functions were used to represent the delay time. Each distribution function includes common random numbers (31 to 36) at the end of the last parameter.

10. Decide whether IM admits a patient or not

Of patients who were examined by IM physicians, 87% were admitted to IM and the rest were admitted to other units or discharged. An entity moves to the true path with probability 0.87 or to the false path with probability 0.13.
REFERENCES


