Improving Electronic Health Record Downtime Contingency Plans with Discrete-Event Simulation

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Abstract

Healthcare has become reliant on electronic health record systems to support patient treatment. Despite all of the benefits of these electronic systems, they have one major flaw: they can go offline, leaving healthcare workers forced to employ contingency plans and procedures. The procedures are poorly regulated and rarely practiced, introducing the potential for significant increase to patient risk. Simulation methods provide a means to examine the problem and develop data derived solutions to make downtime safer. By creating a general simulation model, future study of specific real-world hospitals models and improvements to healthcare organizations can be expedited.

1. Introduction

The wide-spread adoption of electronic health records (EHRs) has brought the implications of system downtimes, which are periods where at least some functionality of the EHR system is not available, to the forefront of healthcare quality and safety [1]. These downtimes can be caused by planned system maintenance and upgrades (planned), or by unexpected loss of connection (unplanned). EHRs, like other health information technologies, are susceptible to system failures. The unavailability of EHRs is disruptive to organizational processes, patient care and, above all, may present serious safety hazards. While well-designed and properly implemented EHR systems have been able to improve the clinical care process with ready and comprehensive access to patient information [2], they have also exposed healthcare delivery systems to the negative consequences of system unavailability.

In the United States, as of 2013, EHR systems had been installed in 70% of hospitals and 72% of private practices [3]. With the prevalence of EHRs, system downtime is a growing area of concern [4–8] and is coming to the forefront of research in health information technology (HIT) and health services management [1,9].

EHR vendors and users are working to prevent downtime events by increasing reliability of hardware and software. Despite these efforts, which are aimed at reducing the frequency and duration of downtime events, healthcare providers will continue to experience downtimes.

In 2012, Hurricane Sandy, although an extreme scenario, exposed the need for detailed and comprehensive downtime planning. The storms caused widespread damage to hospitals in New Jersey and New York which resulted in lost network connectivity and power outages creating unplanned downtimes. In many hospitals, the downtime procedures were in electronic form only and thus not accessible. The hospitals had few staff members present who were capable of enacting the downtime procedures without referencing the unavailable manual [7,10,11]. The situation made it clear that downtime procedures should be well developed and rehearsed to prevent the situation from repeating.

Research on EHR downtime, particularly in acute hospital settings, is in its infancy. We do know that EHR downtimes can be frequent, unpredictable, and pose threats to safety and quality [1,4,6,12]. A study [1] surveying 50 hospitals discovered that almost every responding hospital had experienced some unplanned downtime event within the past 3 years. Seventy percent of the hospitals indicated that they experienced an unplanned downtime longer than 8 hours. Worse still, 3 hospitals responded that downtime was the cause for injuries and negative outcomes for one or more patients.

In order to effectively deliver care to patients, providers must have contingency plans in place to handle EHR downtimes. Yet, there is surprisingly little in the literature or from EHR vendors on best practices for EHR downtimes. Regulatory mandates and recommendations for downtime contingency planning exist (CMS [1], HIPAA [13], IOM [14]), but are vague and insufficient. Regulations simply require that a procedure be on file, but do not specify performance requirements [15,16]. Among healthcare
providers, hospitals are particularly susceptible to downtime events given the complexity of their EHR systems.

Discrete-event simulation provides an opportunity to examine the downtime issue and develop procedures to maintain efficient operations without risk to patients. This paper presents a general simulation model, constructed using approximate and representative data for a medium-sized hospital. The model is motivated by a desire to construct an average and approximate representation of the combined ED and laboratory. The approximation model will be employed to expedite adaptation to real world hospitals to study the impacts of downtime and propose evidence based downtime contingency plans.

2. Background

In order to address downtime issues, two areas of the hospital are identified for their potential to impact patient care. The emergency department (ED) is selected due to its high time sensitive demands for patient treatment. The laboratory is selected due to its high utilization in medical diagnostics and reliance on EHR systems for performing medical testing.

Simulations can closely represent the real world and capture the interactions and variability of human behavior. As such, simulations are becoming increasingly popular in healthcare settings [17–23]. In particular, simulation has been used to improve hospital operations [24–26]. Furthermore, simulations have been used to develop contingency plans, such as in the case of bioterrorism [27,28]. Discrete-event simulation (DES) methods are employed because they most closely mirror the way patient treatment occurs in hospitals. Events such as patient arrival or lab requests, trigger changes in the system’s state at specific points in time and become the building blocks of a DES systems model.

Data collection must be performed to construct the model. Many healthcare operations already have time-based measurements for various operations collected automatically in their EHRs. For gaps that need to be filled, estimations can be made through interviews with healthcare professionals who are familiar with the domain of interest.

2.1. Emergency Medicine

Emergency medicine has been of interest for simulation studies because of the potential for impact in patient safety [25,29–32]. One thing that many of these projects lack is their handling of the ED-Laboratory interface. Many of the ED operations are time critical and delays can put patients at significant risk. Many of the existing studies have focused on the optimal use of ED staff to treat patients as efficiently as possible. Few have considered the impacts of a laboratory slowdown on quality of care.

When a patient arrives in the ED, the staff are trying to assess the patient condition and medical needs. This is frequently done with a round of rapid turnaround tests. Organ function and drug markers need to be screened for in order to know what medications and drugs the patient has in their system, because that influences diagnostic decisions and prescribing. Specimens are collected from the patient and sent to the laboratory. The requested tests are performed in the laboratory where rapid turnaround can be critical to patient treatment.

Simulation has provided a means to examine the intricacies of ED operations without the need to place observers in the ED for extended periods of time and allow for development and testing of alternative procedures without risking patient harm.

Though the ED has been thoroughly explored in the existing literature, the less often investigated interconnected dependencies of the ED and clinical laboratory are of interest for this research. Compared to other units within a hospital, the ED has significantly higher throughput of patients, and represents a major point of entry that is required to stay open even during downtime.

2.2. Clinical Laboratory

The clinical laboratory is the foundation for most of the medical procedures that take place in the modern hospital. An estimated 7 billion laboratory tests are performed in the United States each year [33,34]. Within the hospital, laboratory reports are consulted for 70% of medical diagnostics [33,35]. Emergency medicine is particularly reliant on rapid laboratory testing in order to quickly diagnose patients. Because of the high utilization of laboratory diagnostics and time-sensitivity, delays in the laboratory can be a major source of medical errors that negatively impact patient outcomes [35–38].

Seventy-two percent of providers are currently meeting the meaningful use requirement to have computerized physician order entry (CPOE) integrated into their EHR system [39]. CPOE allows physicians to directly order laboratory tests and other diagnostics. The results of these tests are then communicated back to the physician and care team through the EHR system via the patient’s record.

Emergency physicians rely on laboratory results for clinical decision-making, and any delays or errors in the laboratory can have a dramatic impact on how quickly and safely a patient in the emergency
department can be treated [40]. Because nearly all laboratories rely on CPOE and the EHR system to receive physician orders and to send results back to physicians, any EHR downtime will result in delays in laboratory testing and reporting.

EHR downtime affects laboratory turnaround time. With modern health IT systems capable of reporting test results as soon as they are completed, physicians have become accustomed to the rapid turnaround. During and after a downtime event, turnaround time can extend to hours as the lab falls behind with a backlog of specimens. Typically, the testing equipment in the laboratory is networked into a laboratory information system (LIS), which processes the results and communicates them back to the EHR for physician review. During normal operation, the flagging of critical results on tests are handled based on preset tolerances, and tests are indicated as critical in the EHR before the physician reviews them [35]. During downtime, paper reporting methods become necessary, and results have to be reported to clinicians by fax or phone instead of through the EHR [16]. Physicians waiting for reports are not always notified that the EHR is down and generally are not easily contacted by phone or fax. Consequently, patients in emergency situations, whose diagnosis depends on timely laboratory results, are exposed to significant risks.

Clearly, laboratory availability and turnaround time affects patient safety, but to date, research has primarily focused on clinician and laboratory personnel errors in test selection, execution and interpretation [33,35,36,41–43]. Few studies have focused on the impact of delays in reporting of results [44], and even fewer studies have systematically examined the impact of EHR downtime on the laboratory and other clinical areas, such as the ED, that rely on the laboratory. The nature of the laboratory work lends itself to being modeled in simulation for further study.

2.3. Simulation in Healthcare

Simulations are a frequently used industrial and systems engineering tool for process analysis and improvement. Hospital operations are well-suited for simulation modeling [45–48]. Simulations can capture the complex interdependencies of people, processes and equipment to assess the performance of current or envisioned systems. The advantage of a simulation is that it can quickly, cost effectively and safely – without negatively affecting patients and hospital staff – test and evaluate different process designs.

Despite their suitability and increasing popularity, simulation modeling is still underutilized in healthcare compared to other industries like manufacturing [25]. Another issue addressed by this paper is that typically in ED simulation models the laboratory is treated as a simple time delay step in operations with some probability distribution defining the duration each time it is activated. The model discussed in this paper differs in that it consists of two independent submodels, one for the ED and one for the laboratory. Each of the submodels function on their own for testing and development but can be linked via an interface. The ED generates CPOE requests and specimens, which get sent to the laboratory, the requests and specimens are combined, tested, and results are reported back to the necessary location. With this configuration the impacts of downtime and the link between the ED and laboratory can be investigated via simulation.

In order to understand downtime, the true interconnected nature of the hospital’s different departments and specifically the connection to the clinical laboratory needs to be assessed.

2.4. Data Collection

The development of the model uses a combination of qualitative and quantitative data sources. This triangulation of data has the benefit of enriching data sources and enables data cross-referencing and validation [49–51]. Using multiple and different data sources can also help to reduce problems resulting from missing, incomplete or unreliable data. Triangulation has been used in healthcare research in situations where quantitative data is desired in combination with qualitative data, such as in performance evaluations [52,53].

Many hospitals collect time based performance metrics as part of their existing quality management programs. In the case of the clinical laboratory the Clinical Laboratory Improvement Amendments (CLIA) and College of American Pathologists (CAP) require that the performance be tracked and reported on a regular basis. The regular collection and recording of quality management data means that there is an abundance of archival data that can be statistically analyzed to understand laboratory operations during normal procedures as well as EHR downtime, see Table 1. With these attributes, better decisions can be made about improving metrics such as turn around time, which is the time from test request and specimen delivery to reporting of results [37,40]. Turnaround times are tracked on a monthly basis in the clinical laboratories as part of their internal quality management program [15,33].
Table 1 - Laboratory Metrics

<table>
<thead>
<tr>
<th>Metric</th>
<th>Attribute</th>
</tr>
</thead>
<tbody>
<tr>
<td>Backlog</td>
<td>Number of tests to be processed</td>
</tr>
<tr>
<td>Turn Around Time</td>
<td>Time from testing request to delivery of results</td>
</tr>
<tr>
<td>Accessioning Delay</td>
<td>Time from specimen arrival to accessioning</td>
</tr>
<tr>
<td>Test Start Delay</td>
<td>Time from accessioning to start of testing</td>
</tr>
</tbody>
</table>

Similarly, the EDs have several performance metrics, see Table 2, which are used as a measure of patient throughput. These metrics include the time from patient arrival to patient triage, the time from patient arrival to the time first seen by a physician (door to doc time), and the time from patient arrival to disposition (admit or discharge). These metrics are stored and retrievable allowing the research team to statistically compare these metrics during normal ED operations as well as during EHR downtime operations. Further, the laboratory and ED archival data can be analyzed together to determine how the operations of each domain interact.

Table 2 - Emergency Department Metrics

<table>
<thead>
<tr>
<th>Metric</th>
<th>Attributes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arrival to Disposition</td>
<td>Time from arrival to completion of ED treatment</td>
</tr>
<tr>
<td>Door to Doctor</td>
<td>Time from check in to start of treatment</td>
</tr>
<tr>
<td>Treatment Delay</td>
<td>Time waiting for treatment to start</td>
</tr>
<tr>
<td>Testing Delay</td>
<td>Time waiting for results from the laboratory</td>
</tr>
<tr>
<td>Arrival Rate</td>
<td>Rate at which new patients enter the ED</td>
</tr>
</tbody>
</table>

3. Constructing the Model

First and foremost, it is necessary to declare what the problem of interest is in order to scope the model. The problem is that current downtime contingency plans are suboptimal in terms of patient safety and operational efficiency. The solution to the problem needs to address the current state of hospital operations and facilitate the future modification to real life situations. Additionally it needs to enable the identification and evaluation of procedures that will aid in the mitigation of downtime impacts, and implementation of potential solutions.

In order to have the most flexibility in the finished model, the two areas will be designed and constructed separately and connected via ports and channels. Ports and channels allow for the connected operation of two or more independent models to act together as a larger model of a system. Ports and channels also allow for independent construction and testing, and additionally will facilitate future exploration of downtime in other hospital departments.

To aid in building an accurate model of the laboratory and ED we implemented the triangulated data. Existing research on both areas was combined with published performance data and through interviews with healthcare professionals. Through the triangulation approach, a reasonably accurate approximation of hospital operations can be constructed.

We followed the data-to-decision (D2D) framework introduced by Wernz et al. [54]. Additional general healthcare background that informed this research was from [55–61][#].

3.1. Conceptual Model of the Emergency Department

The emergency department is the entry point for patients into the hospital. Patients need to have their condition assessed quickly and be seen in the order of the severity of their injuries. In most cases physicians send samples from the ED to the laboratory to aid in their diagnostic process and during a downtime incident any slowdown in the communications channels or processing can be dangerous for time critical patients.

Table 3 – Average ESI Distribution of Emergency Patients [63], Treatment Location, and Lab Test Request Probability

<table>
<thead>
<tr>
<th>Triage Rating</th>
<th>Percent of ED Patients</th>
<th>Treatment Start Location</th>
<th>Likelihood Patient Requires Lab Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>ESI 1</td>
<td>1.4%</td>
<td>Trauma</td>
<td>100%</td>
</tr>
<tr>
<td>ESI 2</td>
<td>27.9%</td>
<td>Examination</td>
<td>100%</td>
</tr>
<tr>
<td>ESI 3</td>
<td>29.3%</td>
<td>Examination</td>
<td>90%</td>
</tr>
<tr>
<td>ESI 4</td>
<td>26.0%</td>
<td>Examination</td>
<td>50%</td>
</tr>
<tr>
<td>ESI 5</td>
<td>15.4%</td>
<td>Examination</td>
<td>0%</td>
</tr>
</tbody>
</table>

Upon arrival patients are classified based on a triage system, their condition being assessed by a clinician at the patient’s entry to the ED. For the purposes of the model being constructed, the Emergency Severity Index (ESI) is used. ESI is the triage structure which is most popular in the United States, as of 2009 57% of all hospitals employ ESI as their triage system [62]. The ESI ranks a patient on one of five levels, ESI1 and ESI2 are based on injury severity for patients who are in obvious or threatened
vitals and life respectively. ESI3, ESI4, and ESI5 are classified based on the expected resources required to treat. For example an ESI5 patient will likely only need to be examined while a ESI3 patient will require multiple diagnostic studies to treat [63].

The variety of needs for the different ESI classifications means that patients will likely be seen in different locations within the ED. ESI1 patients will require immediate stabilization for treatment in a specially equipped trauma room staffed by multiple nurses and doctors. An ESI5 patient would only require a simple exam area and being seen by a nurse may be sufficient with only a brief consult from a physician. In this model it is assumed that if samples are taken and sent to the lab, the patient occupies the room until the results come back and are acted on by a clinician. A conceptual diagram of patient flows, based on ESI is in Figure 1 and table of lab request probability by ESI and treatment locations is in Table 3, lab test percentages were obtained based on information provided by healthcare workers.

After accessioning is completed, common activities such as centrifugation are performed as batches before individual testing is conducted. Individual testing is performed by analyzer machines which perform the two most often requested tests; Comprehensive Metabolic Panel (CMP) tests which check for kidney, liver and bone function; and Miscellaneous Chemistry (MC) tests which include checks for auto immune diseases, hormone levels, drugs and cancer markers. For the model it is assumed that CMP tests are always performed before MC.

Once the requested tests are completed, the analyzer machine conducts a validation of the results and automatically flags issues for the workers, the workers still have to review every test regardless of the flag. Under normal operating conditions the results are automatically entered into the patient’s record in the EHR for the requesting physician to review. During the downtime, however, this is rarely the case, and an additional step will be required to fax or call results back to the ED. A figure follows, illustrating the conceptual laboratory work flow.

3.2. Conceptual Model of the Clinical Laboratory

The conceptual model of the clinical laboratory is based on a published model presented by Couchman et al. [64]. Specimens and testing requests typically arrive via a vacuum tube system and CPOE respectively. The initial step is once the specimen and corresponding request are received, they are input into the laboratory’s system via a barcode in a process referred to as accessioning. It is during accessioning that the CPOE request is double checked by the laboratory workers and any unusual requests confirmed with the requesting physician.

3.3. Sub Model Interfaces

In the model, the ED and laboratory will be represented as independent submodels. This submodel structure will allow for faster modification when tailoring this model to a real world hospital. The two subsystems are connected in a manner that allows bi-directional information flow: the ED sends requests to the laboratory, while the laboratory sends results back to the ED.
The clinical laboratory and ED models are constructed independent of each other. Keeping them separate facilitates troubleshooting and development, but also aids in expanding the model at a later time to include more departments of the hospital. To connect the submodels ports and channels are necessary. Requests for laboratory testing are generated by the ED, and ED staff send both a sample and testing request to the laboratory. At the conclusion of the laboratory process, the results of the tests are sent back to the requesting clinician for their review.

One important aspect to include in the interface design is that not all results for tests that originate in the ED will be sent back to the ED. It is often likely that a critical patient has been stabilized in the ED and moved to a different service such as the Intensive Care Unit for continuing treatment. Because patients may be moved, not all completed tests from the laboratory submodel can be sent to the ED, an approximation for how many results should join the output stream for the rest of the hospital must be made.

4. Computational Model Development

In order to construct the computational model of the combined services, data collection for the inputs was necessary. However, since the model is being built in a general case, approximate and representative data was used instead. As part of the triangulation approach, approximate and representative data was collected by reviewing relevant literature, and consulting with subject matter experts to fill in any missing information.

The model is based on a hypothetical medium sized hospital, treating approximately 45,000 patients in the emergency department annually. Most of the data was obtained from Wuerz et al. [63] and Couchman et al. [64] both of which were focused on similarly sized hospitals and have extensive data available. It is expected that much of the data will be re-collected when adjusting the model to a real world hospital. Every hospital has specific characteristics that will need to be reflected in the model, however the general approach used here reflects many hospital scenarios.

The computational model was built and transformed into a dynamic model using Simio simulation software. Simio has been used extensively in healthcare, and in particular ED analysis [30–32,65]. Simio was selected for its object-oriented design and capability of presenting results in 3D animation, facilitating communication of study results to healthcare decision makers [66].

Based on the collected data, approximate and representative hospital operations for normal operations were modeled, the details of the model follow.

4.1. Computational Model: Emergency Department

Patient arrivals in the ED are modeled based on a time independent process. In a real world adaptation of the model, a time-dependent Poisson arrival process would be modeled based on observations at the target hospital. For example, more patients tend to come to the ED on Monday mornings than on Friday nights.

With the data obtained from the literature, distributions were also created for assigning ESI scores to the incoming patients to better match the approximate and representative distributions seen in a real ED (Table 1). The model handles the different patients according to the needs of each ESI group and assigns the limited physician, nurse and room resources accordingly. For the model, priority is given to patients assigned ESI1 and ESI2 scores, the remaining patients scored in ESI3 to ESI5 are seen with a “first-in-first-out” priority logic. A diagram of the ED computational model follows in Figure 3.

Staffing within the ED are modeled as worker objects, this enables their free movement within the system. Doctors and nurses are needed in the different rooms of the ED at different times, their time requirements are built into the work tasks that are completed in each room, ensuring that resources do not get seized for the entire time a patient is in the

**Figure 3 - Computational Model of the Emergency Department in Simio**
room, but only during the duration required. Staff time demands based on ED room are outlined in Table 4.

Table 4 - Staffing Requirements and Patient Interaction Time

<table>
<thead>
<tr>
<th>Location</th>
<th>Nurse (% Time)</th>
<th>Doctor (% Time)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trauma Room</td>
<td>2 (100%)</td>
<td>2 (100%)</td>
</tr>
<tr>
<td>Exam Room</td>
<td>1 (66%)</td>
<td>1 (50%)</td>
</tr>
<tr>
<td>Treatment Room</td>
<td>1 (50%)</td>
<td>1 (33%)</td>
</tr>
</tbody>
</table>

Patients move throughout the ED based on probabilistic paths to ensure the correct percent of patients seen are discharged, admitted or expire during their time in the ED, this is accomplished using the Link Weight and ByLinkWeight logic of Simio.

Requests for the laboratory are created using a Separator object. The separator generates the CPOE request for the laboratory and keeps the corresponding patient in the ED at the WaitForResults combiner, which takes the patient’s test results and merges them back with the patient to continue the treatment process. The separator and combiner do not tag the results in any way that they can be matched to the same patient at both points. For the time being this is a limitation of the model, but only becomes an issue if testing requests are sent with a higher priority that would supersede the first-in-first-out process. The model automatically handles separator and combiner activities as a first-in-first-out logic, given the linear path of the laboratory, this approach should not pose an issue.

Tally Statistics is implemented in the model to enable the collection of the same time based performance metrics that most hospitals use to ensure their quality of service.

4.2. Computational Model: Clinical Laboratory

The interface passes CPOE and specimens from the ED model to the clinical laboratory. Specimens and CPOE requests are treated as having been combined in this model because of the high variability in how laboratories may handle their accessioning or entry of new specimens and requests to their system. In the real world, and especially for downtime models, these steps will need to be included.

As specimens arrive the tests modeled all share a batch centrifugation step, the batching and unbatching are handled via combiner and separator objects. To help simulate a more realistic workload, the laboratory receives specimens and testing requests from other areas of the hospital. Additional requests are modeled as coming from the Intensive Care Unit, other inpatient and outpatient departments, and Cardiac Surgery in addition to the ED. This ensures that there is potential for backlogs in the downtime model and creates a higher fidelity model of the situation.

![Figure 4](image_url) - Computational Model of the Laboratory in Simio

Variability in specimen testing requests are handled with link weights to match the average data collected.

The model interface links the request output of the ED to the specimen reception input of the laboratory model, and the output of the laboratory goes back to the WaitForResults input of the ED to advance patients.

4.3. Implementing Downtime

Downtime is included in the model as a global state variable within a simple sub-system. By modeling downtime events as entities in the system, they can be set to follow a schedule in the same way a planned downtime would, or occur randomly based on a probability distribution, enabling the study of both planned and unplanned downtimes. Once the downtime event is over, the state variable changes to a recovery phase, this allows the model to work through the recovery back to normal operations when downtime backlogs get cleared through and everything returns to steady-state.

Modeling the downtime events in this way allows for the implementation of contingency operations, staffing changes, and adjustments to resource allocations all based on the current system state. It will
5. Discussion

Downtime incidents will continue to impact healthcare. By constructing an approximate and representative model of the interconnected operations of two hospital departments the true impacts of downtime can start to be quantified and understood. At the present time, all that is known is that downtime causes a decrease in efficiency within a hospital.

Testing with the approximate and representative model facilitates exploration of the problem space, and identification of data requirements. Procedures during normal operation do not always work the same in downtime and need to be observed for the variances. A major opportunity for improvement is that currently downtime operations are modeled as a basic delay step due to a lack of real world data.

The benefits of building an approximate and representative model to facilitate future real world simulation research is that gaps in information can be identified before the real world data collection efforts begin. For now, the model makes the possibility of studying hypothetical downtime procedures possible. With influence from healthcare professionals, some contingency plans can be modeled and compared to the existing real world.

![Figure 5 - Relationship between Real and Simulated Systems](image)

The benefits of building an approximate and representative model to facilitate future real world simulation research is that gaps in information can be identified before the real world data collection efforts begin. For now, the model makes the possibility of studying hypothetical downtime procedures possible. With influence from healthcare professionals, some contingency plans can be modeled and compared to the existing real world.

6. Conclusions

The current state of downtime contingency planning is unacceptable, and leaves patients open to unnecessary risk. An approximate and representative model for a hypothetical medium sized hospital was constructed to aid in analysis of the downtime problem. The model features two separate submodels linked together by ports and channels enabling examination of the interdependency of the ED and clinical laboratory. The current model however lacks data to facilitate modeling of realistic downtime due to the need for specific performance data during that time frame. The model constructed does provide a ready built framework for future study of the downtime issue in a real world hospital where true to life data can be collected for downtime operations.

7. References


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