RESEARCH

Is Overtriage Associated With Increased Mortality? Insights From a Simulation Model of Mass Casualty Trauma Care

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ABSTRACT

Purpose: To examine the relationship between overtriage and critical mortality after a mass casualty incident (MCI) using a simulation model of trauma system response.

Methods: We created a discrete event simulation model of trauma system management of MCIs involving individual patient triage and treatment. Model variables include triage performance, treatment capability, treatment time, and time-dependent mortality of critically injured patients. We model triage as a variable selection process applied to a hypothetical population of critically and noncritically injured patients. Treatment capability is represented by staffed emergency department trauma bays with associated staffed operating rooms that are recycled after each use. We estimated critical and noncritical patient treatment times and time-dependent mortality rates from the trauma literature.

Results: In this simulation model, overtriage, the proportion of noncritical patients among all of those labeled as critical, has a positive, negative, or variable association with critical mortality depending on its etiology (ie, related to changes in triage sensitivity or to changes in the prevalence and total number of critical patients). In all of the modeled scenarios, the ratio of critical patients to treatment capability has a greater impact on critical mortality than overtriage level or time-dependent mortality assumption.

Conclusions: Increasing overtriage may have positive, negative, or mixed effects on critical mortality in this trauma system simulation model. These results, which contrast with prior analyses describing a positive linear relationship between overtriage and mortality, highlight the need for alternative metrics to describe trauma system response after MCIs. We explore using the relative number of critical patients to available and staffed treatment units, or the critical surge to capability ratio, which exhibits a consistent and nonlinear association with critical mortality in this model. (*Disaster Med Public Health Preparedness.* 2007;1(Suppl 1):S14–S24)

Key Words: trauma system, triage, hospital surge capacity, emergency medical services

Triage is the systematic ordering of injured or sick patients for the purpose of allocating treatment resources.[1] In various forms, triage is widely used in daily medical care and is considered a critical component of mass casualty response.[2,3] Its use in mass casualty settings reflects the concern that critically injured patients will experience time-dependent morbidity and mortality without appropriate (although not necessarily definitive) medical or surgical treatment. In this context, triage is the process of finding and prioritizing care for critical patients before the proverbial clock runs out and they suffer irreversible harm from their injuries. Although likely inaccurate, the name commonly given to this time-dependent component of mass casualty triage is "the golden hour."[4,5]

Many factors may conspire to prevent the timely delivery of medical treatment to critically injured victims of a mass casualty event, ranging from extrication delays to damage to receiving hospitals. Among these factors, overtriage, which technically is the mislabeling of noncritically injured patients to receive immediate care in a mass casualty setting, but which more commonly has been used as a general metric of emergency department (ED) overcrowding during disasters, has received considerable attention in the trauma and emergency health services literature. In a classic 2002 article analyzing a series of 10 terrorist bombings from 1969 to 1995, Frykberg described a positive linear relationship between overtriage and mortality among critically injured victims of mass casualty events.[6] Based on this finding, Frykberg states that "overtriage could be as life-threatening as undertriage because of the inundation of overwhelmed medical facilities with large numbers of critical casualties all at once which may prevent the timely detection of that small minority with critical injuries who need immediate treatment and jeopardize their survival." (p 207)

This concern has been echoed both in the academic literature and in the definitive clinical guideline for trauma response issued by the American College of Surgeons (*Resources for the Optimal Care of the Injured Patient*, p 13).[2,7–9] Several subsequent reports of mass casualty response have postulated alternative relationships between overtriage and clinical outcomes. Rodoplu and colleagues document 2 hospitals' responses to multiple bombings in Istanbul in 2003, in which both had high overtriage rates, but only 1 experienced critical mortality.[10] Aylwin and colleagues report a lack of linear relationship between critical mortality and overtriage in emergency response to the July 7, 2005 bombings in the London Underground subway system.[11] In both cases the authors note that despite being overtriaged, the hospitals in question retained sufficient capacity to provide high-level care to all of the patients.

The difficulty in predicting when and where a mass casualty event will take place and in capturing the details of the trauma care process in the hectic aftermath of such an event has prevented the conduct of prospective or randomized studies of the role of triage performance and resulting overtriage levels on outcomes of mass trauma care.[12] Several recent efforts to clarify these processes have used computer simulation and mathematical programming techniques to overcome these methodological obstacles.[13–15] The simulation model of single-hospital trauma care created by Hirshberg and colleagues confirms the importance of treatment capability (eg, radiological capacity, staffing levels) in determining the quality of trauma care, which may determine the rates of preventable morbidity and mortality.[13] A linear programming model of triage outcomes developed by Sacco and colleagues explicitly models the differential time-dependent mortality (TDM) of variably injured patients.[14] There have been no studies, however, that systematically investigate the relationship between overtriage and critical mortality, taking into account case mix, triage performance, treatment capability, and TDM for mass casualty victims.

To test the hypothesis that overtriage has a consistent relationship to increased critical mortality after mass casualty incidents (MCI), we created a simulation model that includes 3 essential components of mass casualty care: the number and distribution of patients by casualty type, the triage process, and the treatment capability of the trauma care system. If this model were to show that the relationship between overtriage and outcomes were not consistent, then we would investigate the value of other candidate metrics for describing trauma system surge after MCI. We consider these matters from a trauma systemwide or regional, rather than a single-hospital, perspective, principally to understand the role of systemwide capability constraints on outcomes at various overtriage levels.[16]

METHODS

Model Structure

We constructed a discrete event simulation queuing model of mass casualty care with inputs for event size, patient type (ie, critical vs noncritical), triage test performance, trauma system treatment capability, time requirements for hospital-based evaluation and treatment, and TDM. To highlight the role of overtriage in outcomes in a parsimonious model, we considered only 1 of the several potential queuing-related delays in patient care during an MCI, namely the potential delay after arrival at the receiving hospital due to the unavailability of treatment resources. For simplicity, these resources are represented here by an available and appropriately staffed trauma bay linked, if needed, to an available, staffed operating room; other resources such as radiographic tests are not explicitly modeled, but the time required to conduct these tests is included in treatment time estimates.[13] We did not model patient extrication or transportation time from the site of the MCI to the hospital or the time required to apply the triage test, which commonly is reported to take ≤1 minute.[17] Triage is, in this modeling environment, an instantaneous, test-based ordering of patients that determines the sequence of evaluation once patients reach the ED of a receiving hospital. Figure 1 provides annotated descriptions of the model structure and Table 1 lists the quantitative assumptions underlying each model component, described here. F1 T1

Event Size

We examined the triage and treatment of trauma patients resulting from MCI ranging in size from 50 to 1000 patients; we present detailed results for a baseline event size of 100 total patients both for clarity of presentation and because of the large number of real-life events with total casualties in that range.[6] The proportion of critically to noncritically injured patients (defined by an Injury Severity Score [ISS] ≥15) varies around a baseline value of 25%, consistent with reports of recent mass casualty events in New York, Turkey, London, and Mumbai.[10,11,18,19] Patients are generated simultaneously at the start of each simulation, reflecting an instantaneous injury-causing event such as a bombing.

Triage Test Performance

The model treats triage as a diagnostic test the function of which is to correctly label patients as critical or noncritical, thereby dictating treatment prioritization (ie, with critical patients receiving immediate stabilization and, possibly, damage control surgery and noncritical patients receiving rapid evaluation and expedited management). Although a large proportion of mass casualty victims will self-transport to health care facilities, we assume that arrivals at an emergency department are not treated in a first come-first served manner but rather are assigned a priority at some point before treatment.[20] The current version of this model does not distinguish whether this priority score is applied in the field (ie, by emergency medical service first responders) or by hospital-based clinicians (typically junior or senior surgical staff lo-

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FIGURE 1

Simulation modules and underlying logic of the model. A, Creation and triage of simulated mass casualty patient population; B, hospital-based treatment of simulated mass casualty patient population

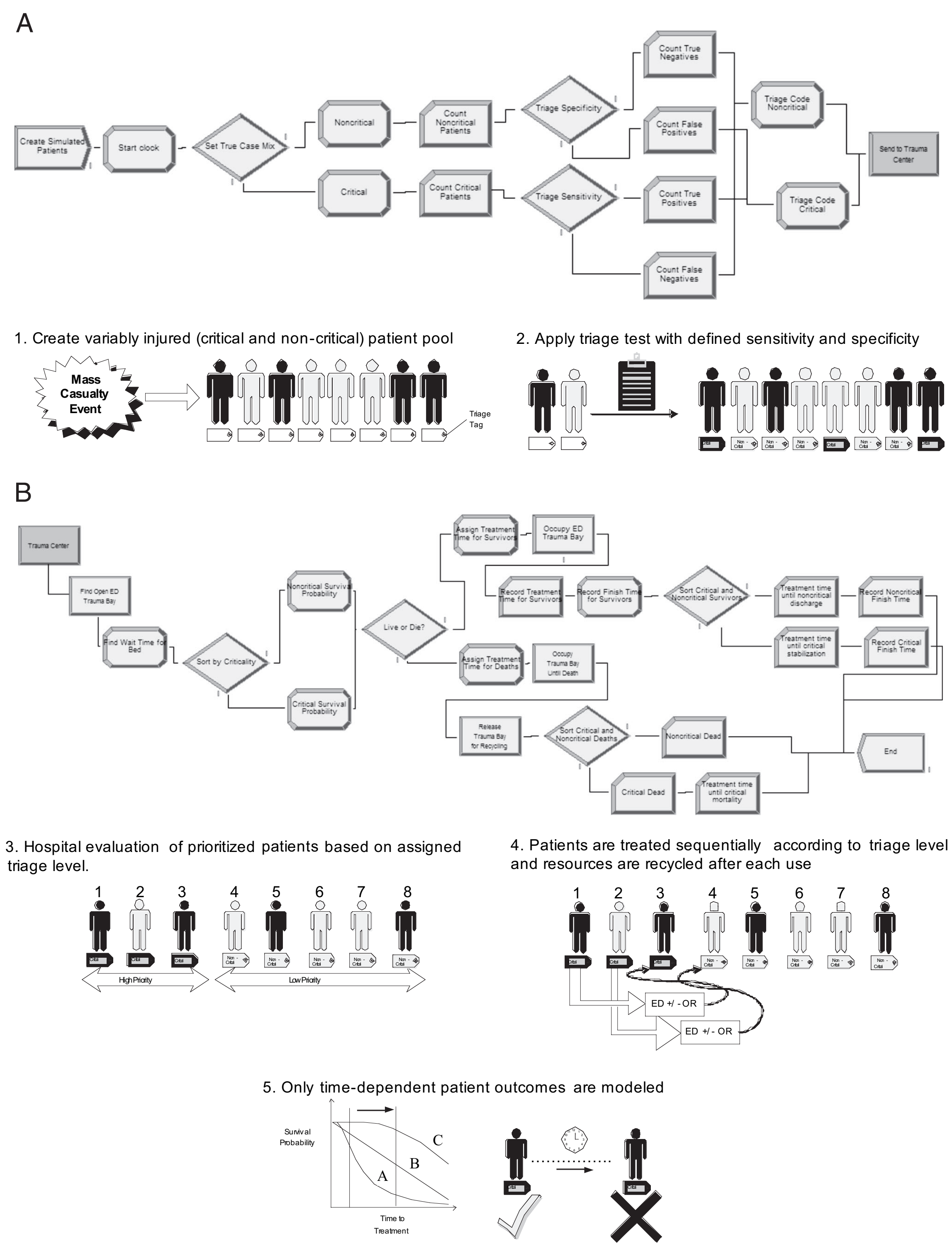

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TABLE 1

Model Assumptions

Variable	Value	Ref
Mass casualty event size	Range: 50–1000 Baseline: 100	6, 8, 10, 11, 18, 19, 28
Proportion critically injured (ISS ≥15)	Range: 8%–50% Baseline: 25%	10, 11, 18, 19
Overtriage due to triage test performance	Range: 10%–59% Baseline: 33%	22
Overtriage due to no. of critical casualties	Range: 14%–65%	N/A (calculated)
Overtriage due to no. of noncritical casualties	Range: 0%–76%	N/A (calculated)
Treatment time		
Noncritical casualties	Range: 5–22 minutes (SD 5–30 min) Baseline: 11 min	23
Critical casualties	Range 120–180 min (SD 30–60 min) Baseline: 175 min	23
Time-dependent mortality	Late: 97% survival first 6 h followed by linear 18%/h decline in survival to baseline of 5% survival Pr(Survival) = −0.184*(delay in hours) + 2.074	22
	Linear: linear decline of 12%/h to baseline of 5% survival Pr(Survival) = −0.1186*(delay in hours) + 1.0632	14
	Exponential: exponentially decreasing survival due to 57% increase in mortality every 10 min waiting in treatment queue, to baseline of 5% survival $Pr(Survival) = [-0.002*(\text{delay in minutes})]^3 + [0.0154*(\text{delay in minutes})]^2 - [0.438*(\text{delay in minutes})] + 100.32$	16

ISS, Injury Severity Score.

cated in the ED receiving bay); the increased complexity caused by events such as surges of walk-in patients unfolding over time will be addressed in future models.[8]

Diagnostic test characteristics commonly are summarized using receiver operating characteristic (ROC) curves describing the relationship of sensitivity and specificity. We found high-quality published sensitivity and specificity data for the most commonly used triage protocol, START, in 1 peer-reviewed article, but this provided only 1 point on a potential ROC curve at 85% sensitivity and 86% specificity.[22] To examine the theoretical range in test performance for START or a START-like triage protocol, we constructed a hypothetical ROC curve manually (see the Technical Appendix data supplement for details) and used the subsequent pairings of sensitivity and specificity for our examination of the impact of triage test performance on overtriage and outcomes.[2,8,17,21,22]

Overtriage

Overtriage may arise from 1 of 2 mechanisms: increasing the sensitivity of a triage test applied to a fixed patient population (ie, with fixed total casualty size and case mix) or decreasing the prevalence of critical patients in a population subjected to a given triage test (ie, with fixed sensitivity and specificity). The second mechanism may be subdivided into cases varying the proportion of critical casualties among a fixed total number of casualties (eg, an enclosed vs open-air bombing) and cases in which the number of critical casualties remains fixed but the total number of casualties changes (eg, events with fewer or more walk-ins). Table 2 shows 3 cases that illustrate overtriage arising from each of these mechanisms, which are described in more detail below.

Application of any diagnostic test will lead to type I (false positive) and type II (false negative) classification errors.[1] Using different scoring cutpoints or thresholds on a particular triage protocol (ie, changing the sensitivity and specificity of the test) will change the balance of type I and II errors. Increasing the sensitivity of triage (eg, lowering the threshold for some clinical or physiological value) will lead to more type I errors, which, independent of case mix and casualty load, will result in calling more patients with noncritical injuries "critical" (ie, increase overtriage). The opposite holds true for increasing the specificity of triage, which will lead to calling more critically injured patients "noncritical" (ie, undertriage). Although it is possible to increase both sensitivity and specificity (eg, by devising an improved triage protocol), for any given protocol there will always be a tradeoff of improved sensitivity at the expense of specificity, and vice versa.

An axiom of evidence-based medicine is that prevalence of disease dictates the clinical consequences of diagnostic test performance.[1] At any given level of triage test performance, therefore, reducing the number of truly critical patients among a fixed total casualty load will increase the likelihood of false positive results, thereby increasing overtriage. Conversely, increasing the number of noncritical casualties around a fixed number of critical casualties (ie, increasing the total event size by adding only noncritical casualties) will also lead to an increase in false positive results, thus increasing

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TABLE 2

Mass Casualty Overtriage Scenarios

Type of Overtriage	Scenario
Due to triage test performance	An underground rail line in a major urban center is bombed, with 2 main access tunnels serving as casualty collection and triage points. An equal number of patients with equal severity of injuries are evacuated from each of the access tunnels. At both sites an experienced trauma surgeon and an experienced emergency medical service provider supervise the assessment and labeling of each patient with a standard triage protocol that includes measurements of consciousness, ventilation, and circulation. At 1 site this team is told that there are several other train stations under attack and that the overall casualty number will be overwhelming. At the other site the triage team is told that only 1 train has been bombed, and that they are looking at the total number of casualties. Acting on this information, the first triage team is much more selective than the second in their designation of critical patients. This results in the second team performing more overtriage in comparison to the first team, simply due to the application of a different cutoff score designating someone as critically injured according to a triage protocol.
Due to decreasing prevalence of critical patients with a fixed number of total casualties	The 2 bombings take place on a commuter rail line, 1 inside a train car and the other at the end of an open platform. Each bombing injures the same total number of people. In each case the same triage protocol is applied in the same manner to sort casualties. The train car explosion produces critical injuries in 25% of its victims, whereas the train platform explosion produces only 8% critical injuries. If the same triage test is performed on each of these patient groups, then the platform (8% critical) casualties will have a higher level of overtriage than the train car (25% critical) casualties.
Due to decreasing prevalence of critical patients with a fixed number of critical casualties	An underground rail line in a major urban center is bombed, with 2 main access tunnels serving as casualty collection and triage points. An equal number of patients with equal severity of injuries are evacuated from each of the access tunnels. Each tunnel entrance is near a hospital, but 1 is a smaller, less well-known hospital and the other is a well-known tertiary care referral center. Casualties assessed and labeled as critical by trained triage teams at each site are transported to the nearest hospital ED, but there is less control over the movement of all of the other patients. Most of these patients, even those who exit the opposite tunnel, self-refer to the emergency department of the well-known tertiary referral center, thereby causing more overtriage when these walk-ins are assessed along with the previously referred patients at this hospital.

ED, emergency department.

overtriage. Unlike standard diagnostic tests for which the triad of sensitivity, specificity, and prevalence of disease are sufficient to fully define test performance, however, triage test performance in the context of the unified trauma system also hinges on the total number of cases, which reflects the total workload on a defined regional health care system. In particular, these 2 methods of increasing overtriage by changing the prevalence of the target condition are not truly equivalent because they change the "critical" workload (specifically the treatment time of all of the critical patients plus those noncritical patients who are listed as critical) resulting from the triage process. Thus, in 1 case overtriage results in a reduction in the critical work (ie, fewer critical patients who make up the bulk of the processing time, whose aggregate decrease in treatment time will outweigh the impact of a larger number of noncritical patients), whereas in another case there is an increase in the critical work (due to more noncritical patients triaged to the critical category and no change in the number of patients with truly critical injuries).

Hospital Treatment Capability

Mass casualty trauma victims with critical injuries may require nonoperative stabilization procedures and operative management of intrathoracic, intraabdominal, or intracranial injuries.[8] Ideally, these patients are rapidly assessed and treated to the extent possible in the ED (eg, via placement of airway, tube thoracostomy, transfusion, radiographic evaluation, exploratory laparotomy) and then, if necessary, are transferred to an open, staffed operating room for expedited surgical care. We therefore defined the unit of critical patient treatment capability as the combination of an open, staffed ED trauma bay linked to an unoccupied, staffed operating room. We based critical and noncritical patient treatment times (from hospital door through completion of operative management) on data used by Hirshberg and colleagues in their single-hospital simulation study.[23] They estimated that critical patients require on average 175 minutes of combined ED and operating room time and that noncritical patients require on average 11 minutes of ED evaluation time. We report data having used normal distributions for these treatment times with means of 175 and 11 minutes and SDs of 30 and 6 minutes, respectively. We investigated the impact of changing the distributions, means, and SDs of these values on outcomes.

Time-dependent Mortality

To estimate the impact of treatment delays on patient mortality, we created 3 TDM curves based on published reports. These represent late critical mortality (97% survival over the first 6 hours followed by a linear 18%/hour decline in survival to a baseline of 5% survival, based on data from Garner et al); linear critical mortality (a linear decline of 12%/hour to the

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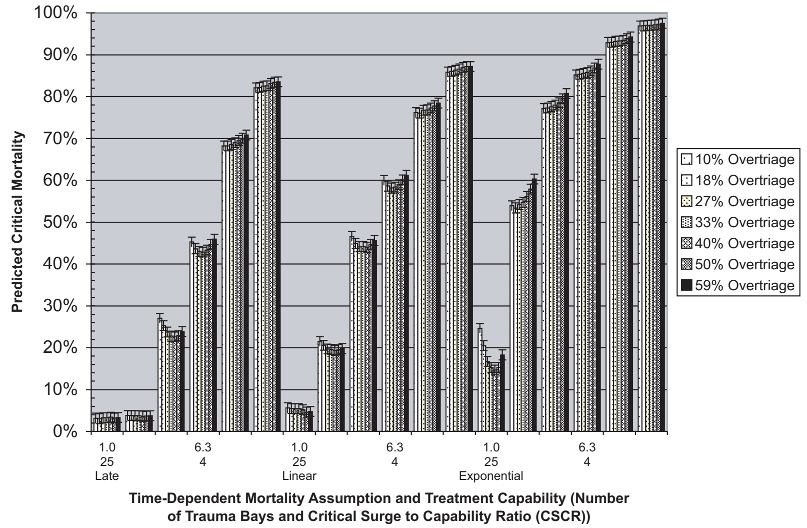
FIGURE 2

Critical mortality due to overtriage resulting from varying triage test performance (N = 100, 25% critical, baseline treatment time, ±95% confidence interval)



5% survival baseline, based on data from Sacco et al); and rapid critical mortality (exponentially decreasing survival due to a 57% increase in mortality every 10 minutes waiting in the treatment queue, based on data from Sampalis et al).[14,16,22] Table 1 summarizes the main assumptions and mortality curve formulas used in the model.

Modeling Software and Replication Parameters

The model was created using the Arena 9.0 discrete event simulation software package (Rockwell Software, Sewickley, PA). A total of 10,000 replications of the baseline case were performed to evaluate the precision of the model output. Results are presented with 95% confidence intervals based on the half-widths generated by 500 iterations of each case, representing the interval in which 95% of results from individual model replications may be expected to fall.

RESULTS

Baseline Scenario Results

The baseline case consists of an MCI involving 100 total patients of whom 25 are critically injured, with a triage process that is 85% sensitive and 86% specific, in a treatment environment that consists of 6 available trauma bays with mean treatment times of 175 minutes (30-minute SD) for critical patients and 11 minutes (6-minute SD) for noncritical patients, with linear time-dependent mortality. When run for 500 iterations with these inputs, the model estimates a critical mortality rate of 44.10% (±1.24% 95% confidence interval); the critical mortality rate estimated with 10,000 iterations is 43.33% ± 0.28%, a 77.4% reduction in variance. Mean time for completion of treatment of all 25 critically injured patients is 7.49 hours and for noncritically injured patients, the mean time is 5.43 hours.

Effect of Overtriage Due to Triage Test Performance

To demonstrate the impact of triage test performance on overtriage and outcomes, we ran the model at overtriage levels ranging from 10% to 59%, corresponding to ROC values generated for the START triage protocol (range of sensitivity and specificity 53%–98%; see Technical Appendix for details). Figure 2 shows model outputs over this range F2 of overtriage for the baseline scenario stratified by treatment capability and choice of TDM curve. Treatment capability is represented in 2 ways: by number of available and staffed trauma bays and by the ratio of critical patients to available trauma bays, noted as the critical surge to capability ratio (CSCR).

The results in Figure 2 demonstrate that in general the difference in outcomes produced by varying triage performance across most levels of treatment capability is minimal. The average range from minimal to maximal predicted mortality for each stratum is 2.76%, equivalent to a difference in <1 additional saved life out of 25 critical patients. The largest effect of triage performance is evident under the exponential TDM assumption at the highest treatment capability level (CSCR = 1), where the maximum range between the highest (at 10% overtriage) and lowest (at 40% overtriage) mortality estimates is 9.96%, equivalent to a difference in outcome for 2 to 3 out of 25 patients.

Insofar as there are discernible differences between overtriage rates at each stratum, Figure 2 is notable for the flat or U-shaped relationship between overtriage and outcomes at a

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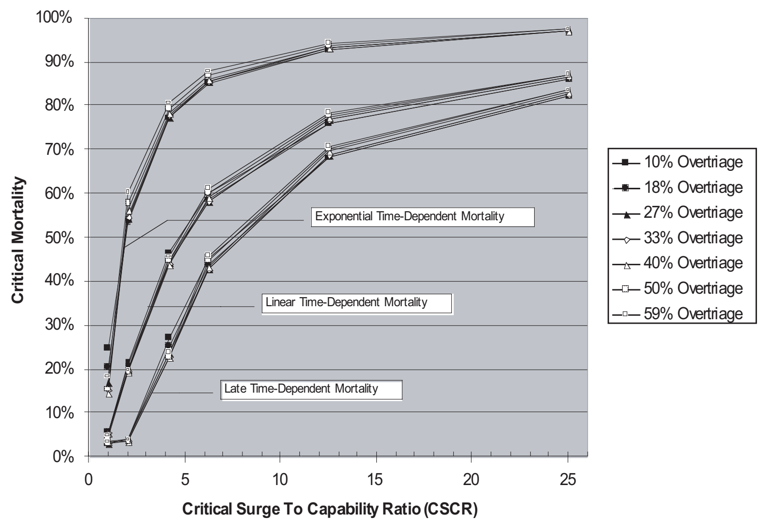
FIGURE 3

CSCR and choice of TDM assumption have a greater impact on critical mortality than variations in overtriage due to triage test performance (N = 100, 25% critical, baseline treatment time, confidence intervals not shown)



number of combinations of treatment capability and mortality assumption. The U-shaped relationship, best seen in the scenarios that produce aggregate critical mortality between 10% and 60%, show that overtriage rates in the 33% to 50% range (corresponding to a triage sensitivity of 85%–95%) produce superior results (ie, lower critical mortality) in moderately resource-constrained environments over a range of TDM assumptions. At the extremes of treatment capability (CSCR = 1 under the late and linear mortality assumptions, 2.1 under the late assumption, and 12.5–25 under all 3 assumptions), the curves flatten, indicating no particular advantage for a specific overtriage level.

Because these results indicate that treatment capability has a much larger effect on outcomes than triage characteristics, we reanalyzed the data in Figure 2 to show the relationship between CSCR and outcomes by TDM assumption (Fig 3). The 3 curves in Figure 3 show the primary importance of treatment capability and the secondary role of mortality assumption in determining outcomes, with only a minor effect of overtriage level due to triage test performance.

Effect of Overtriage Due to Change in Prevalence of Critical Casualties

Having found that overtriage due to triage test performance has a minimal effect on outcomes, we investigated the impact of increasing overtriage by reducing the prevalence of critical casualties. As shown in Figure 4, we found 2 distinct relationships between prevalence-related overtriage and critical mortality. Critical mortality declines when higher overtriage results from decreasing the number of critical patients among a fixed total number of casualties. For example, predicted mortality falls from 65.6% to 8.2% if the number of critically injured patients in a 100-person MCI decreases from 50 to 5, corresponding to an increase in overtriage from 14.2% to 75.7% (under baseline assumptions). In contrast, critical mortality increases with higher overtriage resulting from increasing the total casualty load while holding the number of critical casualties constant. Figure 4 shows that predicted mortality increases from 40.9% to 59.6% as the number of noncritical patients increases from 25 to 975 with a fixed critical patient load of 25, corresponding to an increase in overtriage from 14.4% to 86.7%.

The positive and negative relationships between overtriage and mortality depending on the etiology of overtriage hold under a wide range of treatment capability assumptions, as illustrated in Figure 4 by the similar orientation of curves for each scenario with 4 or 12 as opposed to 6 trauma bays. Figure 5 reanalyzes the data in Figure 4 to clarify the relationship between critical patient load, treatment capability, and outcomes. The 3 scenarios in which the number of critical patients varies display a logarithmic association of critical mortality to CSCR, whereas the scenarios in which only the number of noncritical patients varies appear "stacked" at levels of CSCR that correspond to the ratio of 25 critical patients to 12, 6, and 4 available trauma bays (ie, CSCR = 2.1, 4.2, and 6.3). Because the last 3 scenarios could represent the phenomenon of increasing noncritical walk-ins around a fixed critical casualty load, we sought to clarify further the incremental effect of increasing overtriage in this fashion. Figure 6 breaks out these 3 scenarios by showing the total (left axis) and incremental (right axis) increase in critical mortality with increasing numbers of noncritical patients. This figure shows that over a range of treatment capa-

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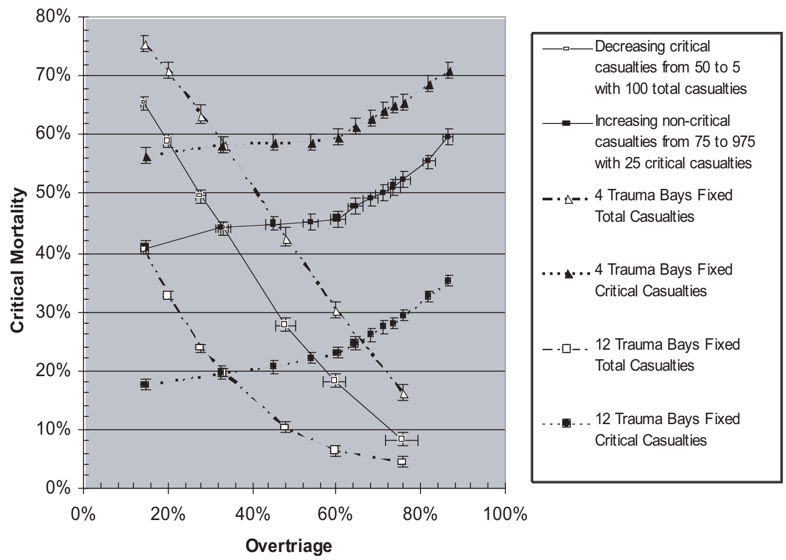
FIGURE 4

Overtriage due to reduced prevalence of critical casualties may increase or decrease critical mortality depending on etiology. (Base case with 6 available trauma bays, linear TDM, and baseline treatment times. 95% confidence intervals are shown for critical mortality [Y axis] and overtriage [X axis] for the baseline 6 trauma bay scenarios.)



bilities, the detrimental impact of walk-ins on outcomes declines with total patient load, so that the 101st patient evaluated in the ED but who is not critically injured has a larger negative impact on critical outcomes than the 1001st patient.

Sensitivity Analyses

We performed analyses to test the robustness of our results with respect to the queuing and processing time assumptions. Running the model under the baseline conditions with a nonprioritized, first come-first served queue (ie, equivalent to a noninformative triage test) produced a 13% increase in critical mortality, equivalent to 1 additional death of a critically injured patient. In contrast, using an exponential vs normal distribution for processing times led to a 16% reduction in critical mortality. Both noncritical and critical patient treatment times had a positive linear impact on critical mortality. In the baseline scenario, each 10-minute increase in noncritical treatment time raises the critical mortality rate by approximately 1.5%, with small variation depending on critical treatment time (range, 1.6% if critical treatment time is reduced from the baseline of 175 minutes to 2 hours; 1.3% if critical treatment time is increased to 4 hours). Each 10-minute lengthening in critical treatment time increases critical mortality by 1.2% (range, 1.2% if noncritical treatment time is 10 minutes; 1.1% if noncritical treatment time is 50 minutes). Changing the SDs of critical and noncritical treatment times yielded minor changes in outcomes; the combination of a large (1 hour) SD in critical treatment and small (6 minute) SD in noncritical treatment yielded the lowest critical mortality (43.3% ± 1.2%), whereas the combination of small (30 minute) SD for critical and large (30 minute) SD for noncritical treatment produced the highest mortality (46.0% ± 1.3%).

DISCUSSION

This simulation model of MCI response captures 2 essential features of trauma care, the expectation that critically injured patients will deteriorate over time and the assumption that there is a limited capacity to treat all patients. Even in such a parsimonious model, we found that overtriage has a complex nonlinear relationship to critical mortality, raising questions about its usefulness as a descriptor of trauma system patient load. We found 3 distinct associations between predicted mortality and overtriage: a small and frequently U-shaped relationship when overtriage is the result of variable triage test performance in a given patient population, a negative relationship when overtriage is the result of a decrease in the number of truly critical patients among a fixed total number of casualties, and a positive relationship when overtriage is the result of a dilution of a fixed number of critical patients among an increasing number of noncritical patients.

Our results highlight the importance of considering treatment capability when discussing the impact of overtriage. In each case the dominant driver of outcomes is the relative balance between the number of critically injured patients and available treatment capacity, a relationship that we propose

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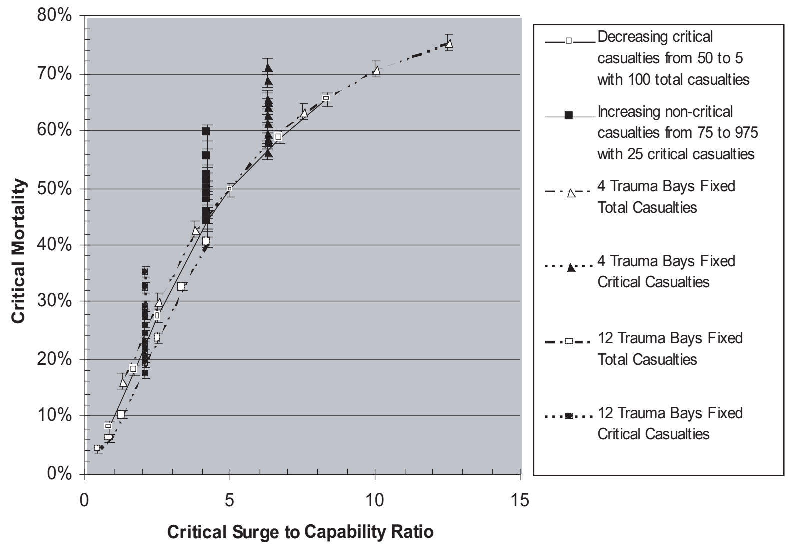
FIGURE 5

Data from Fig 4 reanalyzed to display the relationship between critical mortality and CSCR for scenarios with different prevalence of critical casualties by varying either the number of critical patients (open figures) or number of noncritical patients (filled figures). (Base case with 6 available trauma bays, linear TDM, and baseline treatment times, ±95% confidence intervals shown.)



capturing in a new metric for reporting mass casualty response, the CSCR. A high-CSCR event is one in which the number of critical patients outstrips available treatment resources, whereas a low-CSCR event is one in which resource availability is less likely to play a major role in determining outcomes. Engineers and clinicians who conceptualize surge treatment in terms of throughput will recognize that the CSCR is 1 step toward defining the resource utilization of a trauma system in a single number.

The correlation between overtriage and critical mortality has become a guiding principle in the evaluation and design of mass casualty trauma care systems[7]; however, the very concepts of trauma triage and critical mortality remain poorly defined and inadequately studied. For example, the definition of critical mortality used to assess mass casualty outcomes has been variably defined as the mortality rate among patients presenting with a high ISS (typically ≥15 or 16), completion of nonorthopedic operative management within 24 hours of admission, or admission to an intensive care unit.[18,24,25] "Expectant" patients, referring to those who have such devastating injuries that they are not expected to survive without heroic (and resource-intensive) efforts, are often excluded from calculation of critical mortality in studies of overtriage, even though the proportion of expectant patients may be dictated by the very triage and treatment processes under study (ie, patients with salvageable injuries may become expectant due to delays in operative management).[18]

Overtriage itself has been used as a proxy for discussion of trauma and critical care resource allocation during mass casualty events, whereby high overtriage rates have been taken to imply misallocation of scarce resources away from those patients who truly need it.[9] Our results suggest that this characterization is overly simplistic. Even under the commonly held "golden hour" assumption of clinical decline after critical injury, higher overtriage may be beneficial, as demonstrated by the results for the exponential TDM assumption at the highest treatment capability level (Fig 2, CSCR = 1), showing that predicted outcomes may improve as overtriage rises and correspondingly as undertriage falls. To our knowledge, this is the first report quantifying nonlinear effects of overtriage in a mass casualty response and the first simulation model to document positive effects of overtriage at the trauma-system level.

Accurate reporting on mass casualty response requires the completion of 2 difficult tasks: the assessment of the number of critically injured patients presenting for care and assessment of the availability of treatment resources at the time that those critical patients present. As noted by recent reports on the London and Mumbai terrorist attacks of 2005 and 2006, these are highly dynamic assessments requiring both a new vernacular and new graphical representations of trauma system activation and utilization.[11,19] We believe that the CSCR may prove to be a useful metric in this regard because it has the potential to help standardize the assess-

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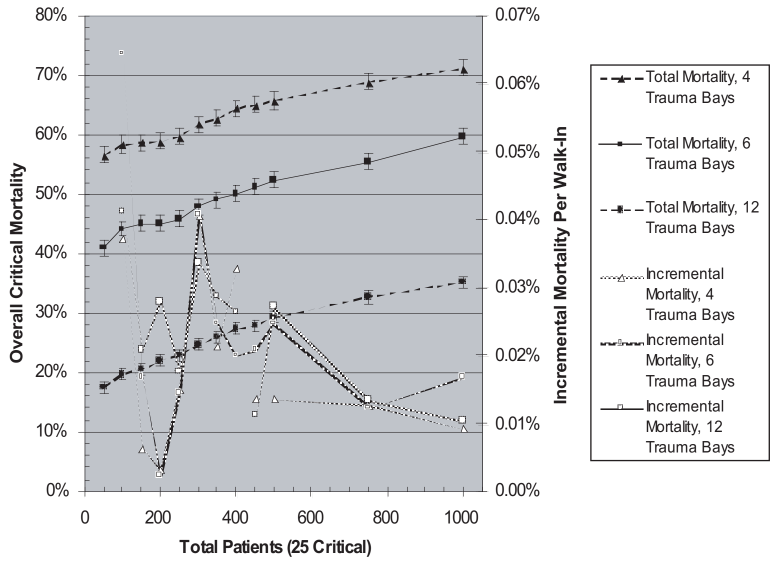
FIGURE 6

Impact of increasing noncritical patients (walk-ins) on critical mortality across different treatment capability levels, showing both overall mortality (left axis, closed figures) and the incremental increase in mortality (right axis, open figures) attributable to each additional walk-in at various MCI sizes. (Base case with 6 available trauma bays, linear TDM, and baseline treatment times, ±95% confidence intervals shown.)



ment of trauma system capacity across mass casualty events of varying size.

The need for an improved theoretical understanding of the genesis and impact of overtriage in mass casualty care is reflected in real-world practices: mass casualty triage and transportation strategies vary widely across the globe, with Israel and the United Kingdom representing ends of the overtriage spectrum. Whereas Israeli emergency medical services put a premium on rapid transport of all patients to hospital EDs for evaluation and treatment with a minimum of field-based differentiation among casualty types, in the United Kingdom field triage and management of mass casualty victims are extensive and may extend to the air transport of trauma surgeons to the incident scene before definitive patient transportation.[11,26,27] If the relationship between overtriage and critical mortality were positive and linear, then an Israeli-type "scoop-and-run" approach would predictably increase the risk of poor patient outcomes for large MCIs. Our model is so highly abstract that caution must be exercised in applying it to any specific real-world scenario. However, it does provide evidence that for a wide range of scenarios defined by treatment capacity and patient mix, increasing overtriage mix led to improved critical care outcomes.

As with any modeling project, this study has a number of limitations relating to the accuracy and realism of model inputs and structure. Despite the prevalence of trauma and specially designated systems for trauma care, there is remarkably little peer-reviewed data on the TDM of critically injured patients. Of the 3 mortality curves used here (linear, late, and exponential), we had to supply the precise shape of the late mortality curve. We use an acutely abbreviated definition of evaluation and treatment of critical injuries (ie, only damage control surgery, not definitive treatment) because of our interest in investigating mortality at the "front end" of MCIs and because critical mortality in this model is the result of delays due to lack of timely access to surgical resources.[25,28] This means that other essential aspects of trauma care, such as radiological procedures, are not explicitly modeled.

In the interest of clarifying the role of triage on critical mortality, we also made a number of simplifying assumptions about critical care (eg, normally distributed treatment times) that may have biased our results. One of the values in developing computer models is that additional features may be added in the future to increase the realism of this simulation.[29] For example, we do not consider realistic factors such as delays in field extraction, ambulance transportation time, hospital delays caused by factors other than queuing for ED or operating room availability, or more fine-grained distinctions between patient types aside from critical or noncritical. We hope to address these and other factors as more detailed information becomes publicly available, and to at-

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tempt to validate a predicted outcome against actual MCI responses.

Overtriage, in this modeling framework, turns out to be an intermediary measure that does not have a consistent relationship with increased critical mortality. In contrast, the ratio of critical patient load and treatment capability tracks nonlinearly but consistently with outcomes, and may prove to be a more useful metric of trauma system response. It is our hope that this model will be 1 of many building blocks to improve the effectiveness of mass casualty trauma systems.

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