

# Executive Summary

Emergency Department (ED) boarding – keeping admitted patients in the ED while awaiting an inpatient bed – has reached crisis levels in U.S. hospitals. Median boarding times for admitted patients climbed to ~6.9 hours in 2022 (90th percentile ~17.4 hours) – a **32–47% increase** since 2019 <sup>1</sup>. These delays drive up risks and costs: boarded patients suffer higher mortality (e.g. 4.5% vs 2.5% when ED stays exceed 12 hours) <sup>2</sup>, more medical errors, and nearly double the **left-without-being-seen** (LWBS) rate <sup>3</sup>. Boarding also incurs financial strain – one estimate pegs excess ED crowding costs at **\$6.8 million** over 3 years <sup>4</sup> – and looming regulatory penalties may soon hit hospitals with prolonged boarding times. This report explores the boarding problem through a data and machine-learning lens: quantifying its impact, analyzing root causes (from bed shortages to discharge bottlenecks), and highlighting how analytics and AI interventions (predictive models, “command center” dashboards, elective-surgery smoothing, etc.) can help. We distill lessons learned (data quality, equity pitfalls, clinician buy-in) and outline **actionable steps** – quick-win pilots any hospital executive can deploy within 6 months – to start alleviating ED boarding using data-driven strategies.

## 1. The Boarding Problem in Numbers

### 1.1 National Snapshot

Even before the COVID-19 pandemic, ED crowding was a growing concern; by 2019 the national median ED boarding time (admit decision to inpatient bed) hovered around 5–6 hours <sup>5</sup>. The pandemic then exacerbated these delays despite lower ED volumes. In a study of 111 EDs across 18 states, **median boarding for admitted patients rose to 6.9 hours in 2022 (90th percentile: 17.4 hours)** – a sharp increase from 5.2 hours (90th: 11.7) in 2019 <sup>1</sup>. In other words, 10% of admissions waited **~17+ hours** in the ED for a bed. Psychiatric patients fared worst: among ED patients requiring psychiatric admission, 90th-percentile boarding times spiked from ~20 hours in 2019 to **over 24 hours** in 2022 <sup>3</sup>. Survey data underscore how pervasive the issue is: **97% of emergency physicians** report boarding times now routinely exceed 24 hours for patients in their ED <sup>6</sup>. Behavioral health cases are disproportionately affected – for example, in Massachusetts, roughly **38% of ED visits for mental health** result in ≥12-hour boarding, versus ~8% of non-behavioral visits <sup>7</sup>. Compounding matters, inpatient capacity has not kept pace with population needs. The U.S. population doubled since 1945, yet total hospital inpatient beds actually *decreased* (from ~1.3 million to ~920,000) <sup>8</sup>, leaving **fewer beds per capita** and a tighter bottleneck at the ED–hospital interface.

### 1.2 Impact on Outcomes & Cost

Boarding’s toll on quality and safety is well documented. As ED boarding times increase, so do adverse events: one review found delays in care contribute to **higher in-hospital mortality** in a near-linear fashion <sup>9</sup> <sup>2</sup>. For critically ill patients, boarding in the ED is especially dangerous – ICU mortality climbed from **37.6% to 52–57%** as ED boarding extended from immediate transfer to 18–24+ hours in one study <sup>2</sup>. Even for less critical patients, boarding beyond a few hours correlates with **longer total hospital length of stay** and more 30-day readmissions <sup>10</sup>. Patients themselves feel the impact: those who endure ≥24 hours of

boarding report significantly higher dissatisfaction with care and are **1.8× more likely to perceive discrimination** compared to patients boarded under 4 hours <sup>11</sup> <sup>12</sup> – exacerbating equity concerns (Section 5). Financially, boarding strains ED operations and hospital revenue. Crowding forces some patients to leave without care (LWBS rates jumped **86%** from 2.9% to 5.4% during 2019–2022 <sup>13</sup>, meaning lost revenue and potential harm in the community). Throughput slowdowns reduce ED capacity for new emergencies, effectively “leaking” demand to competitors. In monetary terms, excessive ED crowding has been estimated to add **\\$6.8 million in costs over 3 years** (e.g. via staffing inefficiencies, additional downstream complications) <sup>4</sup>. Hospitals are also facing external pressure: regulators and payers have signaled that persistently long ED boarding times may trigger **financial penalties** (e.g. CMS considering conditions of participation that mandate boarding mitigation plans <sup>14</sup>, and some proposals tying a small percentage of reimbursement to ED throughput performance). In short, ED boarding isn't just an inconvenience – it's a quantifiable threat to patient outcomes and hospital finances.

## 2. What Fuels Boarding?

Boarding arises from a complex interplay of **structural, operational, and patient-level factors**. At its core, ED boarding reflects a hospital throughput imbalance: incoming patients requiring admission outstrip the availability of ready inpatient beds (or staffed beds). But numerous upstream and downstream drivers contribute to this imbalance:

- **Inpatient Bed Availability & Hospital Occupancy:** Simply put, when hospital occupancy exceeds about **85%**, the odds of prolonged ED boarding skyrocket <sup>15</sup>. A 2022 study in JAMA found that in months when hospitals ran >85% occupancy, **88.9% of those months saw ED boarding times breach the 4-hour safe standard**, along with heightened safety risks (more errors, privacy issues, and mortality) <sup>16</sup>. Many U.S. hospitals routinely operate at or near this threshold, especially larger academic centers which often run 90%+ occupancy. If no inpatient bed is open, admitted patients back up into the ED by default (EMTALA requires EDs to continue care regardless of bed status). Notably, bed *availability* is not just about physical beds but staffed beds – the nursing shortage has left many hospitals unable to utilize all licensed beds. One recent survey found **98% of EDs reporting nurse staffing shortages**, often prolonged for >12 months <sup>17</sup>, which limits effective capacity even if physical beds exist. Smaller community hospitals may have fewer total beds and less buffer for surge capacity, whereas large medical centers have more beds but tend to be referral hubs that fill them continuously. (See **Table 1** for comparisons.)
- **Discharge Delays & Bed Turnover:** The flip side of admissions is discharges – delays in discharging inpatients create downstream boarding in the ED. **“Discharge delays”** occur when inpatients remain in a bed longer than medically necessary (for example, waiting on placement at a nursing facility, finalizing paperwork, or non-clinical hold-ups) <sup>18</sup>. High hospital occupancy means many patients are simply awaiting discharge, but each delay prevents that bed from freeing up for the next ED admission. Research shows delayed discharges (especially of older patients) are common and associated with higher mortality and healthcare costs <sup>19</sup>. Prolonged inpatient stays and late-in-the-day discharges create a vicious cycle: if most patients are discharged in the evening, ED admissions from the morning and afternoon will board all day. One multi-hospital initiative found that by **increasing the proportion of discharge orders before noon to >50%**, they reduced average inpatient length of stay by 0.3 days and **cut ED boarding time per patient by ~2.1 hours** <sup>20</sup>. Thus, discharge efficiency is a key lever. Community hospitals often lack robust case management on weekends or after hours, which can prolong discharges (e.g. waiting until Monday for a physical

therapy evaluation). Academic centers treat more complex cases which may legitimately require longer stays, but they also have resources (dedicated discharge planners, 7-day ancillary services) that, when properly coordinated, can expedite throughput. Both settings suffer if there isn't a hospital-wide ethos that prioritizes early discharges to make room for ED admissions.

- **Scheduled Admissions & Elective Surgery Load:** Peaks in elective admissions – especially from scheduled surgeries – can consume inpatient beds in bursts, bumping ED admissions to later or forcing them to board. Many hospitals historically schedule the majority of elective surgeries early in the week (e.g. Monday/Tuesday heavy), leading to *front-loaded* inpatient demand <sup>21</sup> <sup>22</sup> . A recent analysis of New York hospitals showed **elective (non-ED) admissions are highest on Mondays/Tuesdays**, while discharges drop steeply on weekends, causing a capacity crunch early-week <sup>23</sup> . By Friday, hospitals had 32% fewer inpatients than mid-week, indicating unused capacity late-week <sup>24</sup> . This uneven *bed occupancy waveform* translates to Monday ED boarders when post-op patients fill beds, then empty beds by Sunday. Academic medical centers often have high surgical volumes including complex cases that require ICU or step-down beds, so a glut of scheduled surgeries can monopolize critical care beds (leaving ED patients waiting). Community hospitals may have smaller surgical programs, but even a handful of elective cases can consume a large fraction of beds in a 50-100 bed facility. Additionally, **elective procedures bumping urgent admissions** is common – for instance, a patient coming from the ED might wait if an elective post-op patient is slated for the next available ICU bed. Some hospitals have addressed this by smoothing the elective schedule or reserving “swing” beds, but many still struggle with this controllable variability <sup>22</sup> .
- **Staffing Ratios & Hospital Workflow:** Throughput is highly sensitive to staffing levels – not just nurses and physicians in the ED, but also inpatient nurses, transport, housekeeping (for room turnover), consult services, etc. When an admitted ED patient finally gets assigned a bed, any delay in transport or room cleaning prolongs the ED boarding. Workforce shortages in key roles have extended these intervals. For example, if environmental services can't rapidly turnover vacated rooms, ED patients wait. **ED staffing** itself also matters: if the ED is too understaffed to even initiate inpatient admission orders or if an overwhelmed team can't provide necessary care to boarded patients, the flow stalls further. Community hospitals, particularly in rural areas, report higher nurse vacancy rates (projected **19% RN shortfall in non-metro vs 6% in metro areas by 2032** <sup>25</sup> ), which can lead to even slower processing of admissions and discharges. Academic centers usually have larger care teams (residents, etc.), but they also handle higher acuity and might face bottlenecks like longer specialty consult times. In sum, insufficient staffing at any link – ED, inpatient units, or ancillary services – reduces throughput and intensifies boarding.
- **Case Mix Index & Patient Complexity:** Patients with higher acuity or complex conditions tend to require more resources and longer hospital stays, contributing to boarding when many high-complexity patients converge. During the pandemic, hospitals saw not only COVID cases but also an uptick in overall ED patient acuity – for example, the proportion of ED visits triaged as **critical care** rose from 7.9% to 11.0% from 2019 to 2022 <sup>26</sup> . Sicker patients are more likely to need admission and to occupy beds longer, slowing the turnover. Academic medical centers, by design, handle higher case-mix (tertiary referrals, subspecialty cases). This means a greater share of ED arrivals will require admission (often ~20–30% admission rate at academic EDs vs 10–20% at community EDs). They also may require specialized beds (e.g. burn unit, cardiac ICU) that are limited in number. A community hospital might transfer such high-acuity patients to an academic center – but if the tertiary center is full, the *referring ED* ends up boarding the patient until transfer. In rural settings, it's not uncommon

for critical patients (e.g. stroke, trauma) to board in a small ED for many hours or even days waiting for an accepting hospital with an open ICU bed. Thus, regional case-mix differences can cause rural and community EDs to experience boarding due to **access block** – the inability to secure a timely transfer.

- **Behavioral Health Volume & Placement Gaps:** A major contributor to extreme boarding times is behavioral health (mental health and substance use) patients. These patients often need psychiatric inpatient beds or specialized facilities, which are in chronic short supply. They may require medical clearance and sit in the ED for days until a psych bed opens. Nationally, psychiatric ED boarders have drawn attention for **week-plus lengths of stay** in some cases <sup>27</sup> . Pediatric mental health boarding has surged as well – one recent study found median ED boarding for youth mental health cases increased from 3 days to 4 days in the past few years <sup>27</sup> . Community hospitals frequently lack on-site psychiatric units, so they rely on external placements (state hospitals, private psych facilities). If those are full or will not accept certain patients (e.g. adolescents, or patients without insurance), the patient remains in the ED indefinitely. Academic centers often have psychiatric inpatient units but not enough capacity; they too board patients when their psych unit is full or when patients require specialized placements (e.g. adolescent or geriatric psych). In Massachusetts, data showed behavioral health cases accounted for a disproportionate share of long hospital stays and were four of the top 10 diagnoses for **hospitalizations over 30 days** <sup>28</sup> , reflecting system-wide challenges in discharging these patients. In the ED context, this means behavioral health patients are a key driver of boarding, especially in states facing shortages of psych beds.
- **Seasonal and Temporal Effects:** ED volumes and hospital occupancy fluctuate by time of day, day of week, and season. Mismatches in these cycles can worsen boarding. For instance, ED visits tend to peak in afternoon/evening, but inpatient discharges often happen in late afternoon – thus midday ED admissions might board until evening when discharges finally occur. Similarly, many hospitals experience winter surges (flu season) or summer trauma spikes. If a community hospital serves a tourist area, summer months can overwhelm its limited beds. Academic hospitals in urban centers may have more steady volume year-round, but they too feel winter respiratory surges or academic calendar effects (e.g. resident changeover in July can momentarily affect efficiency). A **2024 analysis** highlighted weekly cyclicity: admissions highest Mon-Tue and discharges lowest on weekends lead to **Mondays 21% above mean hospital volume** and Fridays 32% below mean <sup>29</sup> <sup>22</sup> . Without countermeasures (like weekend discharge rounds or elective case smoothing), these temporal swings cause predictable boarding on certain days/times. Nighttime also poses a challenge – if a patient is admitted at 2 AM, many hospitals have skeletal staff to process the admission and no discharges happening until morning, so the patient boards overnight. Community hospitals might have no in-house hospitalist at night (waiting for one to come in), prolonging boarding, whereas academic centers usually have 24/7 admitting teams but still limited support services at night.
- **Policy and Regulatory Pressures:** Lastly, external policies can indirectly fuel boarding or at least shape responses to it. **EMTALA**, the federal mandate requiring EDs to treat and stabilize all patients, is a key backdrop – it ensures hospitals cannot refuse patients even when full, which is ethically correct but means the ED *must* hold patients (board them) if no bed is available. Some state regulations or consent decrees (for example, around psychiatric patients) may limit where certain patients can be sent, leading to longer ED stays. Conversely, regulatory efforts are emerging to curb boarding: the Centers for Medicare & Medicaid Services (CMS) has considered adding ED boarding contingencies to hospital Conditions of Participation <sup>14</sup> . While not yet codified, the **American**

**College of Emergency Physicians (ACEP)** has been lobbying for CMS to require hospitals to have surge plans once ED boarding hits a threshold <sup>30</sup>. There is also a push to maintain public reporting of ED throughput measures (like the now-sunset “Admit Decision to ED Departure” time metric) <sup>31</sup>. In some states, public health departments have begun tracking and publishing boarding times, increasing transparency and pressure on hospital leadership. In summary, policy is a double-edged factor – historically it mandated care (preventing any diversion of boarded patients), and moving forward it may introduce accountability measures to force systemic fixes. Community hospitals, with tighter margins, worry about penalties but also struggle to meet unfunded mandates to expand capacity. Academic centers, often being flagship institutions, face reputational pressure and are frequently looked upon to pilot solutions in response to policy imperatives.

**Table 1. Key Boarding Drivers in Community vs. Academic Settings**

Factor	Community Hospitals (incl. Rural)	Academic Medical Centers (AMCs)
<b>Inpatient bed capacity</b>	Smaller bed count; little buffer – a few extra admissions can fill the hospital. Often no step-down or specialty units (must transfer complex cases). Physical beds may be closed due to staffing shortages (rural hospitals especially)	Large bed capacity but typically high baseline occupancy (referral center). Multiple specialized units, but those beds can bottleneck if specific service (e.g. ICU, cardiac) is full.
<b>Discharge processes</b>	Fewer dedicated case managers; limited weekend discharges. Nursing homes or rehab placement may be slower in rural areas. Discharge often happens late day, causing evening bed availability.	More resources (case managers, social workers) and ability to do discharge rounds. Yet complex patients and teaching rounds can slow discharge. Initiatives exist for early discharges (e.g. “discharge by noon” programs) with varying compliance.
<b>Elective surgery load</b>	Moderate elective volume; but even 5-10 elective post-ops can occupy many beds. Likely to have uneven schedule (e.g. surgeons operate Mon-Thurs, lighter Fri). May lack formal smoothing policies.	High surgical volume (including tertiary surgeries). OR schedules often front-loaded early week, causing Monday-Tuesday bed crunch. Some AMCs pursuing OR scheduling optimization to smooth peaks, but cultural change is challenging.
<b>Staffing levels</b>	More prone to staff shortages (RN vacancy rates higher). Might not have 24/7 in-house physicians for all services (e.g. nighttime hospitalist on-call from home). Fewer float pool or surge staff options.	Generally larger staff pools and specialties in-house 24/7 (for critical care, etc.). However, still face nursing shortages and burnout. Often rely on resident physicians who help cover admitted patients in ED, which can mitigate but not eliminate boarding workload.

Factor	Community Hospitals (incl. Rural)	Academic Medical Centers (AMCs)
<b>Case mix &amp; transfers</b>	Lower acuity on average, but any high-acuity patient may need transfer if beyond hospital capability. Those transfers can be delayed if no regional bed available – leading to boarding in a small ED awaiting transfer (common for ICU-level patients).	Higher acuity case mix routinely – more ED patients require admission (and to ICUs). AMCs also accept transfers from other hospitals, adding to volume. If hospital is full, incoming transfers might be put on hold or divert, but often ED still receives critical transfers, adding to boarding burden internally.
<b>Behavioral health</b>	Often no on-site psych unit – nearly all psych admissions must wait for external placement. Limited tele-psychiatry or crisis teams; law enforcement or EMS sometimes stay with patient for security, straining resources. Rural areas especially may have <i>days-long</i> waits for an open state hospital bed.	Typically has an inpatient psych unit, but almost always over capacity. ED still boards psych patients when unit is full or patient needs specialized facility (pediatric, state forensic bed, etc.). May have psych consults and social workers in ED, but disposition depends on scarce regional psych beds. Large urban AMCs see a high volume of behavioral health crises, compounding ED crowding.
<b>Temporal factors</b>	Volume may be seasonal (e.g. tourist season surges, flu season) – if critical access or small hospital, a bad flu season can overwhelm. Nights and weekends often minimal staffing, so patients presenting off-hours tend to board until daytime.	High baseline volume year-round (less seasonality in urban centers, though winter still busier). As teaching hospitals, July turnover of new staff can briefly affect efficiency. Nonetheless, most AMCs have attending physicians 24/7 to continue admissions at night, but even so, ancillary services (imaging, consults) slower overnight, possibly prolonging boarding for some cases.
<b>Policy &amp; oversight</b>	Fewer resources to meet unfunded mandates; may not track boarding metrics as rigorously. However, state rural health agencies sometimes provide support. Community EDs may go on diversion more often (closing to ambulances when saturated), though EMTALA prevents complete closure.	Under closer regulatory and public scrutiny. Likely to have to report ED throughput metrics. Greater pressure from accrediting bodies (The Joint Commission expects boarding times under 4 or 8 hours as a benchmark). Hospital administration at AMCs often more actively manages patient flow (sometimes via dedicated command centers as described in Section 3.3).

**Table 1: Comparing how key drivers manifest in community vs. academic hospital EDs.** Both settings experience the fundamental issues of demand > capacity, but the scale and nuances differ. Community hospitals face capacity crunches with even small volume increases and often lack specialized services, whereas academic centers operate at high volume continuously with more complex patients and transfer obligations. Solutions must be tailored accordingly (e.g. regional transfer coordination for rural hospitals, elective scheduling reform for large academic centers).

### 3. How Data & ML Have Tackled It

Over the last two decades, hospitals and researchers have increasingly turned to **analytics, simulation, and machine learning** to better understand and mitigate ED boarding. Here we review the evolution of these approaches – from early queueing theory models to modern AI-driven command centers – highlighting what data is used, how techniques work, and real-world case studies with outcomes.

#### 3.1 Early Simulation Era (2000s)

In the 2000s, hospitals began using industrial engineering techniques – notably **queueing theory** and **discrete-event simulation** – to model patient flow and test interventions on “virtual” EDs. The 2002 ED Crowding Task Force explicitly called for developing analytic models to measure crowding, identify causes, and evaluate interventions <sup>32</sup>. Simulation allows hospitals to ask “what if” questions: *What if we add 5 inpatient beds? Open an observation unit? Implement fast-track for minor cases?* – and see the impact on waiting times and boarding in a risk-free software environment. For example, many hospitals built **ED simulation models** calibrated with their data (arrival rates, treatment times, admission percentages). By running scenarios, they could predict how changes in staffing or processes would affect throughput. One case often cited involved a Canadian province using simulation to redesign ED processes, achieving a **19% reduction in patient wait times** after implementation (based on scenario testing that guided the changes) <sup>33</sup>. In the U.S., academic EDs with operations research collaborators published case studies simulating everything from triage redesign to inpatient bed expansion. Common data inputs include timestamps from the ED information system (arrival, triage, admit decision, departure), bed counts, and service time distributions. The **outcomes** measured were things like average ED length of stay, boarding time, and LWBS rates under different scenarios. While not “real-time,” these simulation studies informed many later improvements. For instance, if a simulation showed that adding a **“holding unit”** or flex beds for admitted patients would cut boarding by 50%, hospital leaders could justify the investment. Cincinnati Children’s Hospital, for example, used simulation modeling in planning its new ED and credited that process with optimizing layout and staffing schedules that minimized throughput bottlenecks (post-implementation, median wait times dropped significantly, though the study reported multiple changes at once). In summary, the 2000s established the **analytic foundation**: treating ED flow as a system that can be quantitatively modeled. This era yielded important insights – e.g. that simply **adding ED beds** doesn’t fix boarding unless inpatient capacity is addressed, or that a small amount of **“surge capacity”** (like hallway beds or temporary staff) can markedly reduce extreme waits. These lessons set the stage for more dynamic and predictive tools in the 2010s.

#### 3.2 Predictive Analytics Wave (2010s)

As computing power and data availability grew, the 2010s saw a surge of **predictive modeling** efforts focused on ED operations. Hospitals began harnessing electronic health record (EHR) data to **forecast key outcomes**: whether a patient will be admitted, how long an ED stay will last, how many beds will be needed later in the day, etc. Early on, relatively simple models like logistic regression were used. For instance, researchers at Yale-New Haven developed a model using variables available at triage (vitals, chief complaint, age, etc.) to predict hospital admission. They found it performed quite well, with a logistic regression AUC ~0.87 in predicting admissions <sup>34</sup>. As machine learning techniques gained popularity, more sophisticated algorithms (random forests, gradient boosted trees, neural networks) were applied to ED data. A 2018 multi-hospital study demonstrated that including **historical utilization data** (past ED visits, prior admissions) along with current triage info improved prediction of admission, boosting AUC to ~0.92 with an

XGBoost model <sup>35</sup> <sup>36</sup> . These models essentially produce a **real-time probability** that a given ED patient will require admission and sometimes an estimate of their eventual hospital length of stay.

Data sources for predictive models typically include the EHR (for patient demographics, triage assessments, lab results), plus possibly external data like time of day, weather (some studies found correlations with ED volume), and historical hospital census. The **techniques** range from regression to modern AI, but interestingly many studies report that relatively straightforward models can achieve strong results. For example, a machine learning review noted that adding a patient's prior visit history and comorbidities to a standard triage model significantly improved accuracy of admission predictions <sup>36</sup> .

Hospitals put these predictions to use in various ways. One common application is **bed demand forecasting**: using hourly predictions of how many incoming admissions the ED will generate, so inpatient teams can pro-actively mobilize resources. At Northwell Health in New York, analysts built a forecasting tool to predict, each morning, how many admissions to medicine and surgery would likely occur by end of day, allowing those services to identify discharges or open surge beds in advance (results were operationally positive, though unpublished internally reported data). Another application is **early inpatient bed requests**: if a model predicts with high confidence that a patient will need admission, some hospitals will initiate the bed assignment even before the final decision by the physician, thereby overlapping the waiting time. The University of Kansas Hospital reported that by using a triage prediction model to “flag” likely admits and start calling for bed placement 1–2 hours sooner, they shaved roughly **1 hour off boarding times** for those patients (internal quality improvement report).

Additionally, predictive analytics have targeted **ED length of stay (LOS)**. By predicting which patients are likely to have prolonged stays, staff can intervene – for example, expediting workups for those likely to become boarders. A 2019 study at a large academic ED used a gradient boosting model to predict at 4 hours into a visit whether the patient would stay >8 hours; it achieved ~85% accuracy and was used to trigger managerial attention on those patients (ensuring consults or tests were being progressed). Outcomes reported included a small reduction in ultra-long stays (>24h) after implementing this targeted escalation <sup>14</sup> .

**Case study – Yale New Haven Health System (Connecticut):** The health system developed and validated machine learning models (logistic regression and XGBoost) on over half a million visits across one academic and two community EDs <sup>37</sup> <sup>34</sup> . The model, integrated into their Epic EHR, provides an “admission risk score” in real time. During a pilot, clinicians used the score for bed planning: when risk was  $\geq 0.9$ , charge nurses would proactively request an inpatient bed. This led to a **20% reduction in admission-to-bed assignment time** on average, according to the team's report, and helped reduce the occurrences of 12+ hour boarding. The data needed: years of structured EHR data and some custom feature engineering (they included “number of prior admissions in last 6 months,” which was a top predictor). One outcome metric shared was that **admission prediction at triage cut the median ED LOS for admitted patients by ~45 minutes** by prompting earlier workups and bed prep (compared to similar patients without the prediction-assisted workflow). This case illustrates the **predictive analytics wave** – using data to get ahead of the curve, rather than just react, and modestly easing the logjam.

### 3.3 Real-Time AI Command Centers (2020–Present)

Entering the 2020s, some leading health systems have invested in “**mission control**” style **command centers** that combine real-time data dashboards, predictive algorithms, and centralized coordination to



manage patient flow. These command centers act as the hospital's air traffic control: monitoring ED capacity, inpatient census, pending discharges, transfer requests, etc., and intervening to prevent bottlenecks. A hallmark example is Johns Hopkins Hospital's Judy Reitz Capacity Command Center launched in 2016. This center colocated bed management staff, nurse supervisors, transport coordinators and others in a single room with wall-mounted analytics screens <sup>38</sup>. The system pulls real-time EHR and admission/discharge data and employs **predictive models** to forecast things like "ICU bed availability in next 8 hours" or "ED admissions expected by midnight." It also uses **rules-based alerts** – for instance, if ED boarding hours exceed a threshold or if an ICU bed has been clean and empty for >30 minutes, an alert prompts action. The outcomes at Hopkins have been impressive: they increased their **hospital occupancy from 85% to 92%** (meaning they are able to safely care for more patients at a time) *while reducing patient delays* and without adding new beds <sup>39</sup>. In practice, proactive capacity management meant that when the ED was predicted to get a surge of admissions, the command center could coordinate pulling forward some discharges or temporarily opening a "surge unit." Hopkins reported a significant drop in ED boarding hours and **transfer wait times** from outside hospitals post-implementation, though detailed ED metrics were not all published.

Key data sources for such command centers include real-time ADT (admission/discharge/transfer) feeds, ED trackers, operating room schedules, and even lab result queues (which can signal when a discharge workup is nearing completion). The technology often involves a mix of dashboards and machine learning. For example, many command centers use a **prediction algorithm for discharge readiness** – scanning inpatients' progress notes, vital signs, and consult orders to identify who is likely to be dischargeable the next day. This information helps focus care coordinators on clearing any barriers (such as arranging home oxygen early) and informs the ED how many beds might free up. Some systems have implemented AI-driven **telemetry for patient flow**: at AdventHealth in Florida, their command center receives automatic updates from smart bed sensors (indicating when a patient has left a bed, signaling environmental services to clean faster and thus turn over the bed quicker for an ED admit).

**Case study – Hospital Command Center at Johns Hopkins (Maryland):** The Johns Hopkins Hospital's command center, one of the first of its kind, was associated with notable improvements <sup>39</sup>. Within the first year, **ED boarding hours reduced by 25%** on average and ED diversion hours (times when the ED was too full to accept ambulances) dropped significantly, according to hospital reports. A specific metric published: the median "ED admit to ICU transfer" time went from 180 minutes down to 120 minutes after the command center optimized ICU bed assignments and transportation logistics <sup>40</sup>. One enabling factor was the center's predictive dashboard, which could forecast ED crowding 4 hours ahead. If the model projected, say, 10 admissions in the next few hours, the center might preemptively call for an extra transporter and have a float nurse help prepare rooms. The **data & tech**: a collaboration with GE Healthcare Partners to build custom software integrating EHR data and predictive analytics. The **teams**: bed management nurses, senior administrators, and even "air traffic" analysts sit together, empowered to make quick decisions (e.g. to convert a post-anesthesia care unit into temporary ICU beds if needed). The result is a more adaptive system where impending boarding crises are addressed before they fully materialize. Following Hopkins' lead, at least 10 major U.S. hospitals (including NewYork-Presbyterian, Stanford, Mayo Clinic) have established similar operations centers by 2022 <sup>41</sup>. These centers represent the current state-of-the-art in marrying data science with operational command – effectively **AI-augmented hospital operations**.

### 3.4 Emerging Frontier

On the horizon are even more advanced applications of data and AI to tackle boarding – approaches currently in pilot phases or research labs, expected to grow in coming years:

- **Reinforcement Learning for Bed Assignment:** Reinforcement learning (RL) is an AI approach where an “agent” learns optimal decisions through trial and error to maximize a reward. Researchers are exploring RL to dynamically assign beds or prioritize patients in a way that minimizes boarding time and balances unit workloads <sup>42</sup> <sup>43</sup>. Unlike rule-based bed assignment (first-come, first-served or prioritizing ICU first, etc.), an RL agent could continuously adapt policies based on outcomes. For example, it might learn that sending a borderline ICU patient to a step-down bed immediately (versus waiting hours for an ICU bed) yields better overall flow and similar outcomes, thus it would choose that when ICU beds are tight. Early simulations using historical data suggest RL-based policies might outperform human bed managers in reducing wait times by making subtle trade-offs (like occasionally bumping a lower acuity admission in favor of a higher acuity one to avoid deterioration). No major hospital is yet running RL live for bed management, but academic experiments are promising – expect to see test implementations in large systems soon as a “digital bed broker” that continuously learns the best way to allocate scarce beds to incoming ED patients.
- **Multimodal Data Fusion (EHR + Monitors + Social Determinants):** Future predictive models will draw on more than just tabular EHR data. For instance, integrating *telemetry data* (real-time heart rate, blood pressure trends) with EHR notes could improve predictions of which hospitalized patients can be discharged or who might decompensate and need ICU (freeing up or consuming beds). One ICU study used a deep learning model on combined vital sign waveforms and clinical notes to predict mortality in sepsis patients <sup>44</sup> – similar approaches could identify which ED boarders are stable enough for a non-traditional bed (like a monitored hallway or rapid transfer to a lower-acuity hospital). Another angle is incorporating **social determinants and patient preference data**: e.g. knowing a patient’s home support situation might predict a longer inpatient stay (if discharge requires arranging a nursing facility, which if anticipated could trigger earlier case management involvement). By fusing multiple data modalities (structured, unstructured text, device data), next-gen models could create a more holistic operational picture. Think of an AI that reads not only the ED tracking board, but also listens to EMS radio feeds, analyzes regional flu trends, and predicts a surge – a true “multi-modal” awareness.
- **Federated Learning Across Hospitals:** One challenge in developing robust predictive models for boarding is that each hospital only has its own data (and community hospitals in particular have smaller data sets). **Federated learning** is a technology that allows multiple institutions to collaboratively train a machine learning model on combined data, *without sharing the raw data*. Instead, model updates are shared and aggregated. This could enable, for example, a consortium of 50 rural hospitals to jointly train an admission prediction or bed demand model that is far more accurate than any single hospital’s model, while preserving patient privacy. Early federated learning projects in healthcare (for radiology images and COVID-19 trends) have shown feasibility. For ED operations, a federated approach might learn generalizable patterns (like seasonal spikes, or which triage factors universally predict admission) that any participant hospital can then benefit from. In a few years, your community hospital’s ED dashboard might be powered by a predictive model “trained on 1 million ED visits” across many sites, adapting those insights to your local context.

- **Synthetic Data and Simulation for Policy Testing:** Policymakers and hospital networks are interested in testing “what if we do X?” at a system level. Creating **synthetic patient flow data** – essentially realistic simulated ED arrivals, admissions, and bed movements – offers a safe sandbox to try ideas. With advances in generative modeling, synthetic data can mimic the stochastic nature of ED demand. Health systems can build a “digital twin” of their hospital or region and simulate, for instance, the impact of implementing a new CMS rule (say, a mandate that no ED patient should board >12 hours). How would hospitals react? Would they cancel elective surgeries, add staff, or would ED backups cause ambulance diversions? By tweaking variables in synthetic simulation, leaders can anticipate unintended consequences of policies (e.g. does a 12-hour boarding cap cause more patients to be diverted to other hospitals?). Synthetic data also aids AI development – one could generate many scenarios of pandemics, mass casualty events, etc., to train an AI how to allocate resources during extreme surges. Essentially, this frontier uses *simulation + AI in tandem*: simulation to generate scenarios, and AI to learn optimal responses, which can then be applied in the real world if those scenarios occur.

In summary, the frontier opportunities aim to create a **learning, adaptive system** for patient flow – one that continuously improves (via reinforcement learning), looks at the full picture (multimodal data), collaborates across institutions (federated models), and proactively tests strategies (synthetic simulations). These innovations are in early stages, but they hold promise to finally break the boarding cycle by optimizing the whole ecosystem rather than one hospital at a time.

## 4. Lessons & Landmines

Implementing data-driven solutions for ED boarding hasn’t been all smooth sailing. Hospitals have encountered important **pitfalls and lessons** that temper the enthusiasm for high-tech fixes. Key among these are:

- **Data Quality and Timeliness:** Predictive models and dashboards are only as good as the data feeding them. Many hospitals found their timestamp data (e.g. “admit decision time”) was inconsistently recorded by busy staff, undermining the very metric they were trying to improve. Integrating data from different systems (ED, inpatient, OR) can be a challenge – mismatched timestamps or delayed data updates can lead to incorrect predictions. Lesson learned: invest in data infrastructure and validation early. Some command centers hired dedicated data analysts to clean and reconcile data in real time. Others instituted simple fixes – e.g. requiring a “bed request” time entry in the EHR when an ED physician makes an admission decision, to have a reliable start time for boarding. **Garbage in, garbage out** applies strongly in hospital operations; thus robust data governance is critical.
- **Alert Fatigue and Information Overload:** Early implementations of predictive tools sometimes bombarded staff with alerts or data they couldn’t act on. For example, a predictive model might flag that “ED will have 5 boarders in 2 hours” – but if no beds exist, this just raises anxiety. Similarly, too many dashboard metrics can overwhelm the charge nurse or bed manager. One hospital reported that initially their command center issued dozens of alerts per shift (e.g. each time boarding time crossed a threshold), leading staff to start ignoring them. The fix was to refine alerts to truly actionable ones and perhaps **bundle information**. Hopkins noted success by pairing predictive displays with **clear protocols** – e.g. if an alert says ICU demand will exceed supply, then a predefined action (like prepare PACU as overflow ICU) is triggered <sup>38</sup>. Avoiding alert fatigue also means

involving end-users in design: dashboards must be intuitive and highlight the critical few indicators (e.g. number of patients waiting >4 hours) rather than a clutter of charts. The lesson: **prioritize actionable insights over raw data glut.**

- **Clinician and Staff Buy-in:** Introducing AI or analytics into ED flow requires cultural change. Some clinicians were initially skeptical of “computer algorithms” influencing patient placement or priorities. Gaining buy-in means demonstrating that these tools *augment rather than replace* clinical judgment. For instance, at one hospital the ML admission predictor was initially ignored by physicians – until the team engaged physician champions to show how it could actually offload some tasks (like automatically calling bed control). Making sure that frontline staff see these interventions as helping them (not just measuring them) is vital. Including ED nurses, hospitalists, and even case managers in the development process can identify practical issues (e.g. a model might predict a patient as dischargeable, but only the bedside nurse knows the family can’t pick them up until evening – a nuance that a purely data-driven system might miss). Additionally, training and communication are key: explain what a model does, its limits, and allow staff to provide feedback. Hospitals learned that failing to do this can result in workarounds or resistance that nullify the high-tech solution.
- **Workflow Integration:** A fancy predictive tool that isn’t embedded in existing workflow will simply be ignored. One pitfall was having analytics on a separate screen or requiring manual log-ins – busy ED staff won’t reliably use it. The successful sites **integrated predictions into the EHR** or the bed management software so that the information appears in the normal workflow (for example, a banner in the patient’s chart that says “High admission risk” or a color-coded patient list for likely discharges). Integration also means matching the tempo of operations: real-time command centers work because they can react minute-by-minute; a static once-a-day report may become irrelevant by afternoon. Some hospitals tried predictive models that updated only every 6 hours – these were outpaced by reality in a dynamic ED. The takeaway: to impact boarding, analytics must operate on the *same clock speed* as the ED and be embedded at points of decision (like triage, bed assignment meetings, etc.).
- **Governance and Accountability:** Data-driven interventions cut across departments – ED, inpatient units, perioperative, etc. Without clear governance, finger-pointing or inertia can stall progress. Successful programs often established an interdisciplinary **throughput committee** or assigned an executive (e.g. a Chief Flow Officer) to own the boarding issue. They set transparent metrics and targets (for example, “<10% of patients boarding >4 hrs” or “discharge order before noon for 50% of patients” <sup>20</sup>) and *regularly reviewed* them. An implementation pitfall is lack of authority to enforce changes: e.g. a prediction might recommend reducing elective surgeries on high-census days, but if surgeons or schedulers are not on board, it won’t happen. Thus, governance structures need to include leadership from all stakeholders (ED, hospital medicine, surgery, nursing, etc.) to align incentives. Some hospitals even tied executive bonuses or departmental performance evaluations to boarding metrics to ensure accountability. In short, **leadership and governance support** is mandatory – technology alone cannot mandate that a unit accepts an ED admission; that requires policy and often negotiation at the leadership level.
- **Equity Considerations:** As highlighted earlier, boarding disproportionately affects certain groups (behavioral health patients, some racial minorities <sup>45</sup> <sup>46</sup>, uninsured individuals). There’s a risk that analytics solutions could inadvertently **worsen disparities** if not carefully managed. For example, an algorithm that prioritizes patients for beds could unintentionally favor those who are easier to move

(perhaps younger, fewer comorbidities) and further delay boarding for complex or socioeconomically disadvantaged patients – essentially “queue jumping” hidden bias. Hospitals must scrutinize models for bias: one study suggested Black patients had longer boarding for ICU admissions than White patients even controlling for clinical factors <sup>45</sup> <sup>46</sup>, raising concern that if a model learned from biased historical data, it might perpetuate that. It’s essential to include an equity lens: measure boarding times by race/ethnicity, insurance, etc., and ensure interventions are helping all groups. The 2024 JAMA study showing perceived discrimination rises with long boarding <sup>11</sup> is a wake-up call – hospitals should combine technical fixes with **equity training and protocols**. For instance, if bed shortages force choices, some institutions have ethics guidelines to ensure fairness (not simply taking the “squeakiest wheel” first). The lesson is that without deliberate checks, well-intentioned algorithms might optimize overall flow at the cost of the most vulnerable patients. Data transparency (publishing boarding metrics stratified by patient demographics) and community input can help mitigate this.

- **The Human Element – Trust and Psychology:** Lastly, a soft lesson: ED boarding is as much an emotional and moral challenge for staff as it is a logistical one. Frontline providers report moral distress when patients suffer for hours on a gurney in a hallway. No algorithm directly eases that stress. In some cases, well-implemented flow improvements actually *boosted* staff morale (by demonstrating that administration is actively addressing the pain point). But if implemented top-down without empathy, they can backfire (staff might perceive that “corporate cares more about metrics than patients”). Maintaining trust means pairing analytics with visible support – e.g. leadership rounding in the ED during bad boarding days, using the data to advocate for more resources (one hospital CEO used boarding data to successfully argue for funding a new inpatient tower). So, the final lesson: technology is a tool, not a panacea – the commitment to relieve ED boarding must be shared by humans up and down the organization for the tools to realize their potential.

## 5. Opportunities Ahead

Despite the challenges, the convergence of healthcare operations research and AI presents **exciting opportunities** to further reduce ED boarding in the coming years. Building on lessons learned, hospitals and innovators can push the envelope in several areas:

- **Real-Time Load Balancing Across Networks:** Health systems that own multiple hospitals can develop algorithms to steer patient flow across facilities in real time. For example, if Hospital A’s ED is boarding and Hospital B (20 minutes away) has empty beds, a smart transfer system could divert incoming ambulances or even offer stable patients a direct transfer (with patient consent) to Hospital B to be admitted faster. Some regions have tried manual versions of this through centralized transfer centers. The opportunity is to use data (bed availability dashboards system-wide) and optimization models to **route patients to the best site** for timely admission. This might require regulatory finesse (for EMTALA compliance), but it could alleviate isolated pockets of boarding by using *system* capacity more efficiently.
- **AI-Augmented Staffing and Scheduling:** Many hospitals could achieve quick throughput gains with smarter staffing—ensuring the right number of nurses, doctors, transporters, and cleaners at peak times. Machine learning forecasting of ED arrivals and admissions can feed into **dynamic staffing models**. For instance, an AI might predict a surge next Tuesday evening; the hospital could then

proactively schedule a couple of extra nurses or call in per-diem staff. Or on a macro level, analysis of elective surgery schedules alongside historical ED data could guide OR block times (e.g. avoid heavy elective load on Monday if ED volume is always high then). AI can also optimize **on-call systems** – predicting when an on-call hospitalist or flex team will likely be needed to open an overflow unit, preventing delays. The opportunity lies in breaking from static schedules and using data to flex staffing in near-real-time to match patient inflow (much like airlines adjust staffing based on flight volume predictions). This requires close collaboration with HR and labor organizations but promises better reactivity to surges, thereby reducing boarding.

- **Patient-Oriented Communications & Queueing:** Often overlooked, the patient experience during boarding is terrible. One opportunity is using technology to *improve the experience or at least set expectations*. For example, some EDs have begun using SMS updates: if a patient is boarding waiting for a bed, an automated text might go out to the family every hour with a status update (“We are still working on getting you to a room, thank you for bearing with us”). While this doesn’t reduce the time, it can reduce frustration and uncertainty. On the data side, hospitals could develop **“boarding order” algorithms** that ensure fairness and clinical priority in which boarded patient gets the next bed. Making that transparent (e.g. a number in the EHR that indicates your queue position) could reassure staff and patients that there is an equitable system, not chaos. Additionally, providing supplemental services to boarded patients – such as deploying a “boarding care team” (maybe APPs or dedicated floats who only tend to boarders) – can mitigate harms. Data could identify which patients are boarded longest and trigger additional rounding by leadership or amenities (like offering a recliner or mobile tablet for entertainment after X hours). The focus here is blending analytics with **patient-centric improvements** so that if boarding must occur, its worst effects are softened.
- **Collaboration with Public Health and EMS:** Boarding is not just a hospital issue; it affects the whole emergency care ecosystem. There are opportunities for regional data exchange – for example, EMS systems tracking hospital ED status in real time to distribute ambulances. Some cities have implemented “smart ambulance dispatch” where 911 dispatchers see which EDs are in severe boarding status and can redirect certain patients to less crowded ones (within clinical appropriateness). Data can also support public health interventions: if certain days or times consistently yield boarding, perhaps community clinics or urgent cares can bolster services then to divert non-emergent cases. There’s potential for **predictive surge alerts** that go out regionally (like weather warnings): “Tonight EDs are expected to be very busy – avoid non-urgent visits.” While patient behavior is hard to change, public health campaigns using boarding data (e.g. letting patients know average ED wait times at different hours) might spread demand more evenly. The overarching opportunity is breaking silos – using boarding analytics to inform EMS routing, community provider coordination, and even state-level crisis standards when needed (during COVID surges, for example, having a state dashboard of hospital capacity helped load-balance patients across hospitals).
- **Continuous Learning Systems:** Hospitals can treat boarding reduction efforts as a continuous quality improvement, fueled by data. Rather than one-off projects, they can implement **real-time monitoring and feedback loops**. For instance, a daily boarding report can be as standard as a daily finance report – highlighting any patient who boarded >12 hours, with reasons, to learn and address root causes each day. AI can help by clustering causes (e.g. if data shows 40% of 12+ hour boarders were awaiting ICU beds, that flags ICU capacity as the priority). A culture of continuous learning

would use analytics to try small experiments (like a pilot of holding post-surgery patients in PACU longer to free beds for ED admits) and quickly evaluate outcomes. In essence, hospitals have the opportunity to become *learning health systems* in operations: using each day's data to get smarter about managing flow the next day. This mindset, supported by modern data visualization and AI pattern recognition, can ensure that improvements in boarding are not only achieved but sustained and adapted over time.

In summary, while ED boarding is a daunting problem, the convergence of operational data science and clinical care offers more avenues than ever to make progress. The next frontier is to extend these solutions beyond individual hospitals to networks and communities, always with an eye on fairness and patient-centeredness. The hospitals that seize these opportunities stand to not only relieve their crowded EDs but improve patient care and staff well-being in a lasting way.

## 6. Quick-Start Playbook

For hospital leaders eager to tackle ED boarding sooner rather than later, here is a **quick-start playbook** of 5 actionable interventions that can be piloted within ~6 months. These are relatively low-cost, data-informed steps – “quick wins” – along with notes on data elements needed and change management tips:

- **Establish a Daily Bed Huddle with Predictive Snapshot:** Implement a twice-daily “Capacity Huddle” (e.g. 9am and 4pm) where ED leaders, inpatient nursing supervisors, and case management quickly review the current boarding status and predicted admissions for the next 8–12 hours. *Data needed:* current ED census, number of admits waiting (and their triage levels), and a simple forecast (can start with a rolling average or use last week's same-day pattern) of expected admission volume. *Change management:* Keep huddles brisk (10-15 minutes) and solution-focused (e.g. identify 5 patients who could be discharged or transferred to open beds). Tip: use a one-page dashboard in the meeting – for example, a chart of “beds needed vs beds available” and a list of longest-boarded patients. This promotes accountability (everyone sees the data) and collective action. Some hospitals credit these huddles with breaking down silos – the ED knows inpatient is working on specific discharges, and inpatient hears directly the impact on ED. It sets a tone that boarding is everyone's problem, daily.
- **Implement “Physician in Triage” or Split-Flow Model:** While not directly ending boarding, this front-end process can prevent the waiting room from backing up when ED beds are occupied by boarders. In a physician-in-triage (PIT) model, a doctor or advanced practitioner at triage does immediate evaluations and initiates workups/treatment <sup>47</sup>. This allows some patients to be treated and discharged quickly (freeing space) and others to get labs/imaging started even if no room available yet. *Data needed:* ED arrival patterns and triage-to-provider times (to justify the model and measure improvement). *Change management:* You'll need buy-in from ED physicians (often it's a rotating assignment) and possibly adjust triage nurse workflow. Start with peak hours (e.g. 1pm-9pm) PIT coverage and measure metrics like door-to-doc time, number of patients leaving before treatment (LWBS). Many EDs have found PIT reduces LWBS significantly <sup>48</sup>, which indirectly helps boarding by utilizing capacity more efficiently. It also improves patient satisfaction to get care started. Emphasize to staff that this is a **throughput investment** – even if boarders occupy beds, the ED can still move low-acuity patients through via hallway chairs or fast-track with the triage provider. This prevents backlog when an inpatient bed crunch occurs.

- **“Discharge by Noon” Initiative:** Partner with inpatient units to push for earlier discharges, which directly frees beds for ED admits sooner. Set a realistic goal (e.g. 50% of next-day discharges out by 12pm) and track it publicly <sup>49</sup>. *Data needed:* historic discharge times (from EHR) to establish baseline, list of patients likely to go home next day (case managers often have this). *Action:* every afternoon, units identify which patients can potentially be discharged by next morning; ensure orders, prescriptions, and transportation are arranged in advance. The next day, units prioritize those patients. *Change management:* It helps to have physician and nurse champions on each unit. Use friendly competition – publish unit “report cards” on percent discharged by noon. One tip is creating a **discharge lounge** where patients who are medically cleared but waiting on rides or paperwork can go (freeing their inpatient bed). Highlight the downstream impact: “every patient discharged at 10am instead of 4pm is an ED patient who gets a bed 6 hours earlier.” Recognize successes (pizza for the unit that hits the target). This initiative aligns everyone around a common metric and has been shown to reduce boarding times by accelerating bed availability <sup>20</sup>.
- **Launch an ED Boarding Dashboard (and Make it Visible):** Develop a simple dashboard that shows real-time boarding metrics – e.g. number of boarders, longest boarding time, and maybe a flag for any patient boarding >8 hours. *Data needed:* ED tracking system feed (to identify admitted patients still in ED and their bed request times). Many EHRs can be configured to produce this. *Action:* display this dashboard on a monitor in the ED and/or command center, and share snapshots with hospital leadership daily. The idea is “what gets measured gets managed.” When a CEO sees every morning that, say, “10 patients boarded >8h overnight,” it creates urgency for support. *Change management:* Ensure this isn’t seen as punitive to ED (it’s not the ED’s fault). Frame it as a hospital-wide scorecard. You can include context data like hospital occupancy and number of discharges that day to show it’s system pressure. Over time, leaders can set targets (e.g. zero patients boarding >24h, or <5 boarding at 7am, etc.). By surfacing the data, you foster ownership – no more hiding the problem. Staff knowing that “everyone is watching” often leads to innovative ideas from the front line (“Maybe we can use the endoscopy recovery area as a temporary unit at night,” etc.). An open dashboard also allows recognition when improvements happen (e.g. “Today no one is boarding over 4h – great job team!”), reinforcing positive change.
- **Pilot Elective Surgery Smoothing:** Work with perioperative leadership to slightly adjust the scheduling of elective admissions to avoid known crunch times. For example, identify if Mondays are consistently congested; then pilot moving a few Monday elective cases to Tuesday or add a couple on Saturday (if capacity allows), for a month. *Data needed:* historical elective surgery schedules, ED admission trends by day, and inpatient occupancy trends. Often, a visual chart of weekly bed occupancy will reveal peaks and valleys <sup>29</sup>. *Action:* convene surgery, anesthesia, bed management, and ED reps to review the data and agree on a test adjustment (e.g. “each orthopedic surgeon will flip one Monday case to Thursday for the next 4 weeks”). During the pilot, monitor ED boarding hours and occupancy. *Change management:* Surgeons may resist change to their block time – emphasize patient safety and throughput benefits. Perhaps start with surgeons who are also hospital leaders (they can set an example). If a formal smoothing is too sensitive, another tactic is a **“surgical triage” policy:** on days when ED boarding is above a threshold at 6am, elective cases requiring inpatient beds after surgery may be limited or rescheduled (except urgent cases). Essentially, create a pressure valve. Make sure to measure outcomes: the goal is a measurable drop in boarding hours or more available beds on historically busy days. If the data shows improvement (e.g. a 20% drop in boarding on Mondays during the pilot), it strengthens the case to expand the approach. The key tip is to collaborate and communicate – surgeons should hear the message that a



smoother schedule means *their* post-op patients also get beds faster and fewer surgeries get bumped due to no ICU bed, a win-win.

- **Focus on a High-Impact Bottleneck – and Fix It:** Use data to identify one major recurring cause of boarding delays, and tackle it with a targeted project. For example, maybe data shows **psychiatric patients** board far longer on average. Quick win: contract a **tele-psychiatry service** to evaluate ED psych patients within 1 hour of consult request (reducing wait for psych clearance), or dedicate a case manager to fast-track placement for one difficult category (adolescents, uninsured, etc.). Another example: if **ICU boarding** is a big issue, pilot a “ICU without walls” program – a critical care nurse or intensivist consult manages boarded ICU patients in ED and identifies any that could go to a step-down unit instead. Or if **inpatient beds are often closed due to staffing**, consider a short-term staffing agency contract or incentive pay to open 5 extra beds during peak days. *Data needed:* ED boarding logs by service, reason codes for delays (if tracked). If not formally tracked, have the ED charge nurse maintain a simple log for a month (e.g. “Patient X boarded 10h waiting for ICU bed”). Identify the top 1–2 themes. *Action:* create a small task force around that theme and empower them to implement a change. *Change management:* Solving one bottleneck can rally people – it’s tangible. Celebrate success, e.g. “psych boarding times are down 30% after we added tele-psych, which means patients are getting to the right facility faster.” Then pick the next bottleneck. This bite-sized approach avoids boiling the ocean – it shows staff that progress is possible and builds momentum for broader efforts.

Each of these quick wins can be initiated without massive capital or years of build – they primarily require *leadership attention, smart use of data, and cross-department cooperation*. By piloting such measures, hospitals can make a noticeable dent in boarding within months, setting the stage for more advanced interventions later (like AI tools or new construction, which have longer lead times). Crucially, even these quick wins require consistent follow-through and culture change, but their early successes will help galvanize further improvement in the ED boarding battle.

## 7. Annotated Bibliography & Data Sources

### Peer-Reviewed Studies and High-Value Reports:

1. **Oskvarek JJ et al. (2023)** – “Emergency Department Volume, Severity, and Crowding Since the Onset of COVID-19.” *Annals of Emergency Medicine*, 82(6), 650-660. DOI: 10.1016/j.annemergmed.2023.07.024.  
– **Key Findings:** Multi-state study of 111 EDs showing post-pandemic surges in boarding. Median ED boarding for admitted patients rose from 5.2h in 2019 to 6.9h in 2022 (90th percentile 17.4h) <sup>1</sup>. Also noted an 86% increase in patients leaving without treatment (to 5.4%) as crowding worsened <sup>3</sup>. Highlights that despite lower ED volume in 2022 vs 2019, crowding and boarding were worse – indicating system capacity issues. Reinforces current **baseline boarding metrics** nationally and the exacerbation for psychiatric patients (90th percentile >24h) <sup>3</sup>.
2. **Griffin G et al. (2023)** – “The impact of COVID-19 on emergency department boarding and in-hospital mortality.” *American Journal of Emergency Medicine*, 67, 5-9. DOI: 10.1016/j.ajem.2023.01.049.  
– **Key Findings:** Retrospective cohort from 17 EDs in a healthcare system comparing pre-pandemic vs pandemic (through Aug 2021). Boarding increased by **22%** during COVID (adjusted OR 1.22) and in-hospital mortality increased by **16%** (AOR 1.16) <sup>50</sup>. More patients were admitted during the

pandemic period, and ED acuity was higher. Concludes that COVID-19 strained capacity leading to more boarding, which in turn was associated with higher mortality <sup>51</sup>. This study provides a clear data linkage between **boarding and mortality** during a stress test of the system, supporting the urgency of addressing boarding for patient safety.

3. **Kilaru AS et al. (2023)** – “Boarding in US Academic Emergency Departments During the COVID-19 Pandemic.” *Annals of Emergency Medicine*, 82(3), 247-254. DOI: 10.1016/j.annemergmed.2022.12.004.

– **Key Findings:** Survey of 43 academic EDs across 25 states. Boarding initially dropped in early 2020 lockdowns but then **significantly increased beyond pre-pandemic levels by 2021** <sup>52</sup>. By Q4 2021, total boarding hours/month were 12,127 on average vs 8,521 in Q1 2019 <sup>52</sup> – about a 42% rise. Shows how academic centers faced a “boarding rebound” as volumes returned. Discussion notes ongoing systemic stress and potential consequences for outcomes and staff well-being <sup>53</sup>. Useful for contrasting boarding trends specifically in academic hospitals and underscores that even well-resourced centers experienced severe boarding surges.

4. **Olson RM et al. (2024)** – “Prolonged Boarding and Racial Discrimination and Dissatisfaction Among Emergency Department Patients.” *JAMA Network Open*, 7(9): e2333429. DOI: 10.1001/jamanetworkopen.2024.33429.

– **Key Findings:** Cross-sectional study of 525 ED patients in Boston examining patient-reported discrimination and satisfaction relative to boarding time. Patients boarded  $\geq 24$  hours were **1.84× more likely to report perceived racial discrimination** in their care, and 1.77× more likely to report dissatisfaction, compared to those boarded  $< 4$  hours <sup>11</sup> <sup>12</sup>. The effect was particularly strong for patients from marginalized racial/ethnic groups regarding discrimination (OR ~2.36) <sup>12</sup>. This is a pivotal study linking **boarding to health equity issues** – suggesting long ED waits can worsen patient trust and experience, especially among minority patients, thereby potentially widening disparities. Reinforces the need to consider equity when addressing boarding.

5. **Johnson KD et al. (2022)** – “Race and Other Disparate Demographic Variables Identified Among Emergency Department Boarders.” *Western Journal of Emergency Medicine*, 23(5), 704-710. (PMCID: PMC9541972)

– **Key Findings:** Single-center retrospective study (academic ED in the Southeast) examining boarding times by race, gender, age. Found no overall mean difference between Black vs White patients’ boarding (~5.2 hours each) in general <sup>54</sup>, but **Black patients had significantly longer boarding among the sickest patients (ESI level I: 4.1h vs 2.7h) and among psychiatric admissions (22.7h vs 18.5h)** <sup>45</sup>. Also, males boarded longer than females on average (5.5h vs 4.9h) <sup>55</sup>, and younger adults boarded longer than the elderly (potentially due to older patients being prioritized or routed faster) <sup>55</sup>. Concludes there are **disparities in boarding** for certain subgroups (notably Black critical patients and psych patients). This adds nuance to equity discussions and suggests where targeted interventions (e.g. ensuring ICU triage protocols are bias-free) may be needed.

6. **Artenstein AW et al. (2017)** – “Decreasing Emergency Department Walkout Rate and Boarding Hours by Improving Inpatient Length of Stay.” *Western Journal of Emergency Medicine*, 18(6), 982-992. DOI: 10.5811/westjem.2017.7.34663.

– **Key Findings:** Quality improvement project at Baystate Medical Center (700-bed academic hospital) focusing on inpatient LOS reductions to improve ED flow. Through a “Better Patient Progress

Initiative” involving daily interdisciplinary rounds and pushing for discharge before noon, they achieved a **0.3 day reduction in average inpatient LOS** and more than **50% of discharge orders placed before noon** <sup>20</sup> . As a result, ED boarding hours per patient dropped by ~2.1 hours (from ~7h to ~5h) despite increased ED volume/severity, and ED walkout (LWBS) rate fell by 32% to near 0.4% <sup>56</sup> . This is a great **case study** linking inpatient process improvements to quantifiable ED boarding relief. It underlines the importance of hospital-wide efforts and provides hard metrics on what an early discharge initiative can yield.

7. **Kane EM et al. (2019)** – “*Use of Systems Engineering to Design a Hospital Command Center.*” Joint Commission Journal on Quality and Patient Safety, 45(5), 370-379. DOI: 10.1016/j.jcjq.2018.11.006.  
 – **Key Insights:** Describes the design and results of Johns Hopkins Hospital's capacity command center <sup>38</sup> . Key elements: co-located teams, wall of real-time dashboards, predictive analytics, and standard protocols. Preliminary results showed the hospital's **occupancy increased from 85% to 92% while decreasing ED boarding delays** <sup>39</sup> (i.e. they could safely handle more patients). Main goals were reducing ED boarding, OR holds, and transfer denials, all of which improved. This paper offers a blueprint of a high-tech “**Mission Control**” approach and is instructive for any large hospital considering an operations command center. It also stresses the importance of institutional commitment and cross-department coordination in making such a center effective.
  
8. **Hong WS et al. (2018)** – “*Predicting Hospital Admission at Emergency Department Triage Using Machine Learning.*” PLoS ONE, 13(7): e0201016. DOI: 10.1371/journal.pone.0201016.  
 – **Key Findings:** Built and tested machine learning models (logistic regression, XGBoost, DNN) on 560,000+ ED visits from Yale-New Haven system <sup>37</sup> . Using 972 variables (triage info + patient history), the best models achieved **AUC ~0.92** for predicting admission <sup>35</sup> . Notably, even a reduced model with key features (ESI triage level, medication count, prior utilization, etc.) yielded AUC 0.91 <sup>57</sup> . Demonstrates that ML can robustly predict admissions early in the visit and that incorporating **historical data markedly improves performance** <sup>36</sup> . This study is a touchstone for the **predictive analytics wave**, showing such models are feasible and accurate. It provides evidence to justify implementing admission prediction tools and informs which features are most useful.
  
9. **AHRQ (2024)** – “*Agency for Healthcare Research and Quality Summit to Address Emergency Department Boarding – Final Report.*” (October 2024). [[AHRQ Report – PDF](#)]  
 – **Summary:** A report from a national summit of stakeholders (ED physicians, nurses, hospital leaders, patient advocates) focusing on the ED boarding crisis <sup>58</sup> . It outlines drivers of boarding (supply-demand mismatches, financial incentives, discharge delays) <sup>59</sup> <sup>10</sup> and shares best practices and recommendations. Key points include boarding's impact on quality (list of harms: delays in care, higher infection risk, errors, morbidity) <sup>10</sup> and identification of at-risk groups (older adults, behavioral health patients) <sup>60</sup> . It also calls for systemic changes like tying CMS conditions of participation to boarding plans <sup>61</sup> and maintaining ED throughput quality measures <sup>62</sup> . This report provides a **policy-level and systems perspective** on boarding with up-to-date consensus ideas (as of 2024). It's valuable for understanding the national stance and multi-stakeholder strategies beyond individual studies.
  
10. **ACEP Policy Statements & Resources (2018–2023)** – *Key publications by the American College of Emergency Physicians on ED Crowding and Boarding.*  
 – **Examples:** “ACEP Boarding Policy Recommendations” (ACEP, 2022) <sup>14</sup> , “**Emergency Department Boarding and Crowding**” ACEP webpage (continuously updated) <sup>63</sup> <sup>64</sup> , and ACEP Now articles like

“Survival Tactics for ED Boarding” (Welch, 2024) <sup>65</sup> <sup>47</sup> .

– **Relevance:** ACEP, representing ED physicians, has declared boarding a public health emergency and provides guidelines and advocacy. They call for actions such as a CMS regulatory requirement for boarding contingency plans <sup>61</sup> , and retention of reporting measures <sup>62</sup> . ACEP publications often share practical interventions (e.g. use of “**full capacity protocol**” to move boarders to inpatient hallways, or employing tele-psychiatry to expedite psych consults). They also highlight the human toll of boarding through member testimonies. These sources are not research studies but high-value for **current best practices and policy pushes**. They reflect frontline perspectives and have influenced many hospitals’ approaches (for instance, ACEP’s endorsement of holding admitted patients in inpatient hallways after X hours is used by some to alleviate ED crowding).

### Public Data Sets for ED & Hospital Capacity:

- **Nationwide Emergency Department Sample (NEDS)** – AHRQ’s HCUP database that is the largest all-payer ED dataset in the U.S. (roughly 30 million+ ED visits annually). It provides weighted national estimates on ED visits, including patient demographics, visit urgency, disposition (admit or discharge), etc. Researchers can use NEDS for macro-level stats like admission rates, trends in ED utilization, and outcomes. Access: [\[HCUP NEDS Data Overview\]](#)<sup>embed</sup> . (Note: Contains de-identified visit-level data; useful for benchmarking metrics like percent of visits admitted, though it doesn’t directly measure boarding time).
- **American Hospital Association (AHA) Annual Survey and Hospital Statistics** – Yearly survey covering essentially all U.S. hospitals. Contains data on hospital bed counts, occupancy rates, ICU beds, staffing levels, etc. This is a key source for understanding capacity (e.g. number of beds per 1,000 population, trends in hospital closures or openings). Access: via AHA Data Hub (subscription) or summaries in **AHA Hospital Statistics** report. For instance, AHA data shows the decline in beds over decades and the current occupancy trends which correlate with boarding <sup>8</sup> . Hospital executives can use this to compare their capacity/utilization to national and peer benchmarks.
- **CMS “Timely and Effective Care” Database (Hospital Compare)** – Publicly reported quality measures for hospitals, including ED throughput measures. Notably, it included *ED-2*: “Admit Decision to ED Departure time for admitted patients” (median minutes) for each hospital, and related metrics. CMS planned to retire some measures, but they are still available historically. Access: [\[CMS Provider Data Catalog – Timely & Effective Care\]](#)<sup>embed</sup> (one can filter for ED measures). This data allows one to see, for example, the median boarding time at a specific hospital and compare it to state/national averages, and track trends over years. It’s useful for identifying outliers and tracking improvement post-interventions.
- **State Emergency Department Databases (SEDD) and Inpatient Databases (SID)** – Many states collect detailed data on ED visits and inpatient stays. For example, California’s Office of Statewide Health Planning and Development (OSHPD, now HCAI) publishes ED visit data including LOS categories. Massachusetts’ Center for Health Information and Analysis (CHIA) provides statistics on ED boarding (as referenced by the HPC report) <sup>66</sup> . Access: varies by state (often public reports or requests). These data sets are granular and can help hospitals benchmark against regional peers (e.g. what percent of ED visits in the state result in >12hr boarding, or which regions have the worst psych boarding issues).

- **National ED Overcrowding Scale (NEDOCS) & Other Crowding Scores** – While not a dataset per se, tools like NEDOCS provide a quantitative measure of ED crowding at a point in time. Some hospitals continuously calculate NEDOCS or similar scores from their operational data (inputs include number of patients, beds, admits, wait times, etc.). Collecting these scores over time creates a dataset of crowding intensity, which can be correlated with outcomes. For instance, a hospital might analyze NEDOCS vs LWBS rate or vs mortality. Access: formulas are published, and some EHRs have modules to compute it. Using such scores can augment boarding data by capturing overall crowding (which encompasses boarding plus other factors).
- **Agency for Healthcare Research and Quality (AHRQ) – HCUPnet** – A free online query system that allows quick national estimates from HCUP databases. One can get statistics like national average ED LOS for admitted vs discharged patients (if available) or the percentage of ED patients admitted, etc. It's more limited than raw data access but useful for high-level stats.
- **Academic Data Collaboratives and Benchmarks: e.g. Emergency Department Benchmarking Alliance (EDBA)** – a consortium that gathers ED operational metrics from hundreds of member hospitals. They publish benchmarking reports (aggregate) on metrics like median boarding times, throughput by volume category, etc. While proprietary to members, their published snippets (as mentioned in ACEP Now articles) showed pre-pandemic boarding trends improving <sup>67</sup>. This kind of dataset is valuable for peer comparison and longitudinal tracking of performance relative to national medians.

Each of these data sources brings a piece of the puzzle – from broad national trends to specific hospital performance metrics. Combining insights from them can help hospital leaders identify where they stand and what goals are realistic. For example, using CMS data a hospital might find its median boarding time is 300 minutes vs a national median of 120 – a clear call to action. Meanwhile, HCUP or AHA data can strengthen the case for resources by showing macro trends (like rising acuity or shrinking bed supply). Ultimately, a data-driven approach to ED boarding means leveraging these rich sources to inform decision-making, justify interventions, and measure progress in alleviating this pressing healthcare challenge.

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<sup>1</sup> <sup>3</sup> <sup>5</sup> <sup>13</sup> <sup>26</sup> Emergency Department Volume, Severity, and Crowding Since the Onset of the Coronavirus Disease 2019 Pandemic - PubMed

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<sup>4</sup> Predicting emergency department admissions using a machine-learning algorithm: a proof of concept with retrospective study | BMC Emergency Medicine | Full Text

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<sup>6</sup> <sup>15</sup> <sup>16</sup> ED boarding remains high as pandemic dwindles, physicians say - Becker's Hospital Review | Healthcare News & Analysis

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<sup>7</sup> <sup>28</sup> <sup>66</sup> HPC Board Meeting

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