

The Benefit of the Doubt Phenomenon in Emergency Triage Assignment Disparities

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Abstract

Emergency department (ED) triage decisions critically impact patient care and are standardized, yet ethnoracial disparities in triage assignment are well documented. We analyzed ethnoracial differences in triage assignments across four U.S. EDs (two adult, two pediatric), comprising 1.4 million encounters from 2011–2025. To better characterize these disparities, we developed an automated triage algorithm that replicates the Emergency Severity Index (ESI) criteria, the standard triage protocol used at each site. The algorithm identifies high-acuity symptoms and danger-zone vital signs that inform triage decisions at the level-2 (emergent) versus level-3 (urgent) boundary. We compared nurse triage assignments across ethnoracial groups, stratified by algorithmic ESI scores, using causal inference methods to adjust for clinical presentation and hospital context. Significant ethnoracial disparities in triage assignment were observed across all sites. Disparities were concentrated among patients algorithmically classified as lower risk but assigned higher acuity by nurses. This pattern is consistent with a “benefit-of-the-doubt” disparity, in which relatively stable, non-Hispanic White patients are more often assigned higher priority than Hispanic and non-Hispanic Black patients with comparable presentations. By contrast, disparities were attenuated or absent among patients deemed high risk by both nurses and the algorithm. Finally, analysis of the projected length-of-stay impact of substituting nurse-assigned with algorithmic triage scores suggests that algorithmic ESI decision support could reduce triage disparities with minimal effects on patient flow.

Keywords: emergency, triage, fairness, demographics

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060 1 Main

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062 Nearly two decades after the Institute of Medicine declared emergency departments (EDs) to be “at the
063 breaking point” [1], overcrowding continues to strain U.S. EDs [2–4]. There were 155.4 million visits to
064 U.S. EDs in 2022, roughly 47 per 100 people [5]. All ED visits begin with nurse triage, a process that
065 assigns urgency and shapes downstream care (e.g. admission, length of stay). Consequently, even small,
066 unwarranted variation in triage assignment may contribute to disparities in timeliness of care, length of
067 stay, and mortality risk [6].

068 To reduce such variation, healthcare systems have adopted standardized triage protocols intended
069 to support objective, repeatable assignments. The most widely used is the Emergency Severity Index
070 (ESI) [7, 8], developed in 1998 and used in 94% of U.S. EDs as of 2019 [8]. ESI is a five-level scale
071 intended to reflect urgency and risk of deterioration (1- immediate, 2- emergent, 3- urgent, 4- semi-
072 urgent, 5- non-urgent). ESI is determined from clinical characteristics, including “high-risk” symptoms
073 and “danger-zone” vital signs, and does not explicitly incorporate sex or race/ethnicity.

074 ESI is intended to standardize triage assessments, yet studies show frequent misapplication (59%
075 accuracy [9]) and high inter-rater variability [10, 11]. Moreover, the process of assigning ESI scores may
076 be susceptible to bias. Retrospective studies report that Black and Hispanic patients may be assigned
077 less urgent scores than White patients [12–15], potentially contributing to longer waits, less comprehen-
078 sive evaluation, misallocation of resources, and fewer admissions. Assignment practices also vary across
079 sites, and the questions used to elicit and document patient status vary across triage nurses [16]. To
080 reduce unwarranted variation, it is critical to identify where bias may enter the triage decision pathway,
081 particularly at the boundary separating *high-acuity* patients (ESI 1–2) from *lower-acuity* patients (ESI
082 3–5), who can generally wait to be seen.

083 This requires identifying the conditions under which disparities in triage assignment arise. We hypothe-
084 sized that ethnoracial disparities would be enriched in pathways that (1) carry less apparent clinical
085 risk and (2) rely more heavily on subjective clinical judgment. We tested these hypotheses by implement-
086 ing an automated ESI algorithm and generating algorithmic scores for approximately 1.4M encounters
087 from four U.S. EDs over a 15-year period (Fig. 1). This enabled stratification of nurse-assigned triage by
088 agreement with handbook criteria and finer separation of apparent high- versus low-risk visits. We then
089 used causal inference methods to estimate the association between ethnoracial identity and the odds of
090 receiving an emergency (ESI 2) nurse triage assignment, stratified by algorithmic ESI assessment.

091 We analyzed 1,381,873 encounters at four EDs serving adults on the East (AE: 398,661 encounters)
092 and West coasts (AW: 116,063 encounters) and children on the East (PE: 339,400 encounters) and
093 West coasts (PW: 527,749 encounters). The cohort was diverse (30.8% Non-Hispanic White, 12.6% Non-
094 Hispanic Black, 36.7% Hispanic, 5.1% Asian, and 10.4% Other); see Table S1. We focused on encounters
095 assigned ESI levels 2 and 3, which comprise the majority of visits and represent the critical boundary
096 between emergent (ESI 2) and urgent (ESI 3) care (Fig. 1E). This boundary is also strongly associated
097 with admission likelihood (Fig. 1E) and is therefore a setting in which clinician judgment can meaningfully
098 shape downstream care. Accordingly, the final cohort included encounters assigned ESI level 2 (AE:
099 33.2%, AW: 23.6%, PE: 24.5%, PW: 15.3%) or level 3 (AE: 53.9%, AW: 65.5%, PE: 47.1%, PW: 27.7%)
100 at triage, totalling 342,232 (AE), 103,029 (AW), 242,734 (PE), and 226,864 (PW) encounters. Additional
101 cohort details are provided in Table S1.

102 Comparison of nurse-assigned and algorithmic ESI scores showed substantial discordance (Fig. 1F),
103 particularly for algorithmic ESI level 2, consistent with subjectivity at the level-2/3 boundary. To assess
104 the validity of algorithmic assignments, we compared admission rates conditional on nurse-assigned and
105 algorithmic ESI scores (Fig. 1G). Encounters assigned nurse level 2 were *less* likely to be admitted
106 when the algorithm assigned level 3, and conversely, encounters assigned nurse level 3 were *more* likely
107 to be admitted when the algorithm assigned level 2 ($p < 6.1e-3$, Mann–Whitney–Wilcoxon test, two-
108 sided). These results support that the ESI handbook algorithm captures clinically meaningful severity
109 information beyond nurse-assigned triage.

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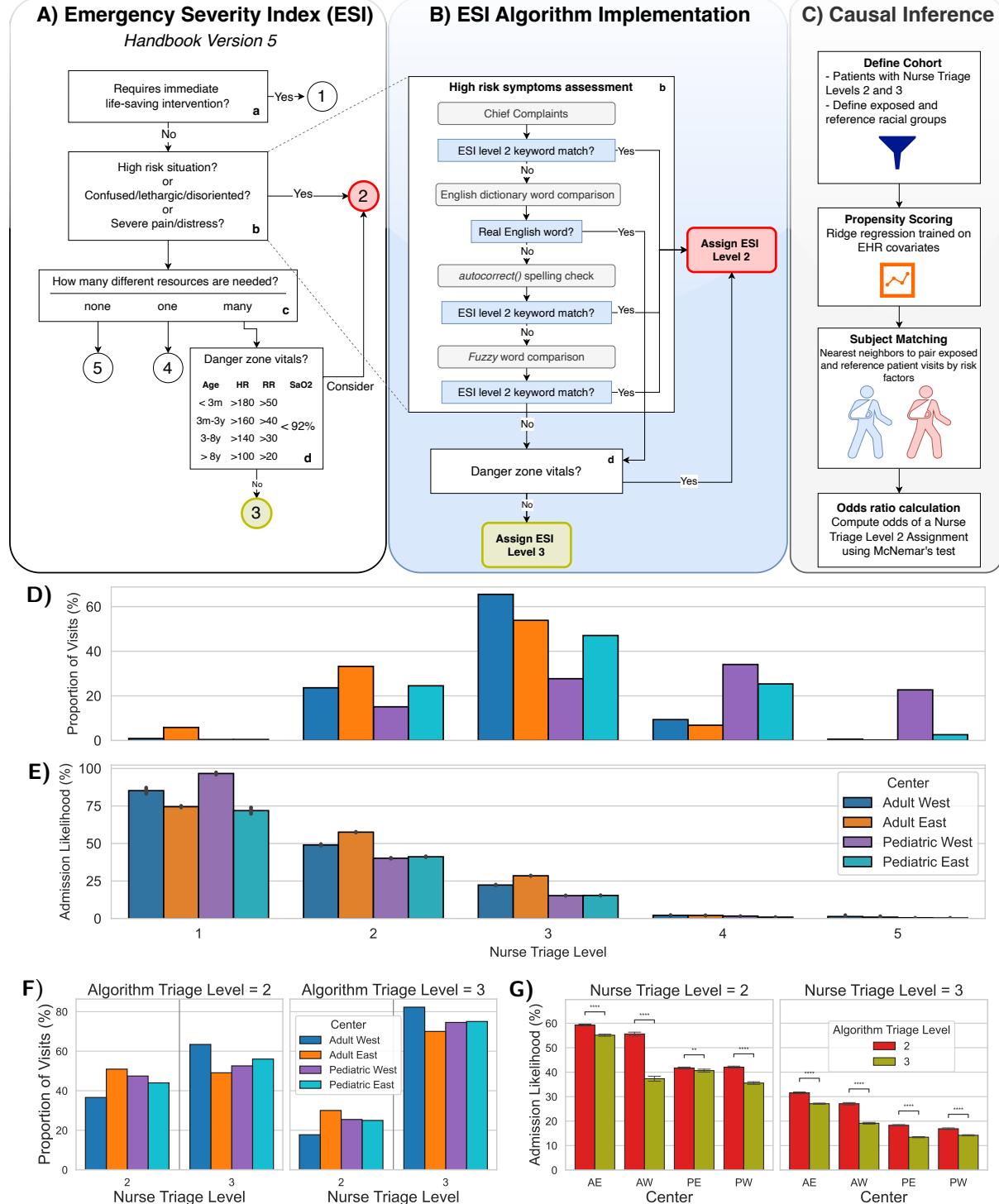


Fig. 1 Emergency Severity Index (ESI) algorithm implementation and validation. **A)** Original ESI algorithm flowchart with triage levels 2 and 3 highlighted in red and green, respectively. **B)** Computational implementation of ESI algorithm levels 2 and 3, including high-risk symptom detection (box b) and danger-zone vital sign detection (box d). Algorithm ESI levels 2 and 3 are highlighted in red and green. **C)** Propensity score matching pipeline workflow. **D)** Distribution of nurse-assigned triage levels. Levels 2 and 3 are most common overall. **E)** Nurse-assigned triage level is associated with admission. Patients assigned high acuity (levels 1–2) are more likely to be admitted than those assigned levels 3–5. **F)** Concordance between algorithmic and nurse-assigned triage at levels 2 and 3. Roughly half of algorithmic level-2 encounters are assigned nurse level 3, whereas algorithmic level-3 encounters more closely agree with nurse assignments. **G)** Algorithmic ESI provides diagnostic information beyond nurse-assigned triage. Encounters assigned a more urgent algorithmic score than the nurse-assigned score are more likely to be admitted (right panel), and vice versa (left panel), across sites. *p*-value annotation legend: *: $1.00e-02 < p \leq 5.00e-02$; **: $1.00e-03 < p \leq 1.00e-02$; ***: $1.00e-04 < p \leq 1.00e-03$; ****: $p \leq 1.00e-04$.

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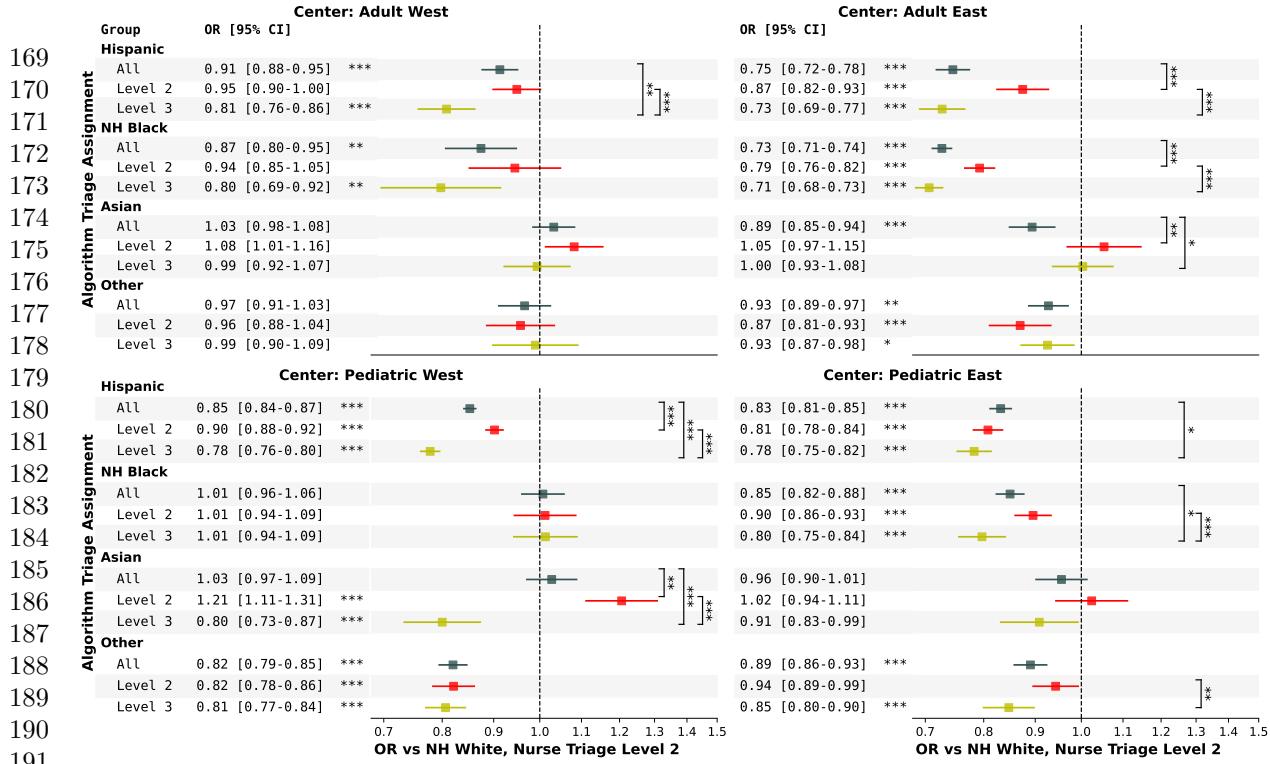


Fig. 2 Ethnoracial disparities in emergency triage assignment by algorithmic ESI assessment. Odds ratios of receiving a nurse-assigned ESI level 2 (emergent) relative to Non-Hispanic White patients. Each subplot represents a care center (AW, AE, PW, PE). Results are shown for Hispanic, Non-Hispanic Black, Asian, and Other groups (y-axis). Results are further stratified by algorithmic triage assignment (y-axis). Adjusted odds ratios (ORs) are shown with 95% confidence intervals (CIs). Statistical significance of differences relative to Non-Hispanic White patients is denoted by asterisks in the test column accompanying the ORs. Additional within-group tests compare ORs across algorithmic triage levels and are denoted by vertical asterisks. *p*-value annotation legend: *: 1.00e-02 < *p* <= 5.00e-02; **: 1.00e-03 < *p* <= 1.00e-02; ***: 1.00e-04 < *p* <= 1.00e-03; ****: *p* <= 1.00e-04.

We estimated the odds of receiving a nurse-assigned ESI level 2, relative to propensity-matched Non-Hispanic White encounters, stratified by ethnoracial group and algorithmic triage level (Fig. 2). Across centers, Hispanic and Non-Hispanic Black patients generally had lower odds of nurse-assigned level 2 than matched Non-Hispanic White patients. For Hispanic patients, odds were lower at all centers (OR, AW: 0.91 [0.88-0.95]; AE: 0.75 [0.72-0.78]; PW: 0.85 [0.84-0.87]; PE: 0.83 [0.81-0.85]). Similarly, Non-Hispanic Black patients had lower odds at three of four centers (AW: 0.87 [0.80-0.95]; AE: 0.73 [0.71-0.74]; PE: 0.85 [0.81-0.85]).

When stratified by algorithmic triage level, disparities were more pronounced among encounters assessed as lower risk (algorithmic level 3). Hispanic patients had reduced odds of high-acuity triage compared to matched Non-Hispanic White patients at all centers (AW: 0.81 [0.76-0.86]; AE: 0.73 [0.69-0.77]; PW: 0.78 [0.76-0.80]; PE: 0.78 [0.75-0.82]). Non-Hispanic Black patients showed similar patterns at three of four centers (AW: 0.80 [0.69-0.92]; AE: 0.71 [0.68-0.73]; PE: 0.80 [0.75-0.84]). By contrast, among algorithmic level-2 encounters, disparities persisted but were generally attenuated for Hispanic patients at three centers (AE: 0.87 [0.82-0.93]; PW: 0.90 [0.88-0.92]; PE: 0.81 [0.78-0.84]). Non-Hispanic Black patients likewise showed reduced but persistent disparities at two centers (AE: 0.79 [0.76-0.82]; PE: 0.90 [0.86-0.93]). Overall, patients assessed as lower risk by the algorithm (level 3) exhibited larger disparities than those assessed as higher risk (level 2) across multiple centers (Hispanic: AW, AE, and PW *p* < 0.001; Non-Hispanic Black: AE and PE *p* < 0.001).

A more granular analysis of alignment between algorithmic ESI and nurse-assigned triage revealed site-specific differences in how ESI level-2 criteria were applied. The ESI algorithm first evaluates high-risk symptoms and then danger-zone vital signs when determining level 2. However, centers differed in the relative contribution of these factors to nurse-assigned level-2 decisions (Fig. S1). In the Western

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adult and pediatric centers (AW and PW), nurses more often assigned level 2 in the presence of danger-zone vital signs than high-risk symptoms. Conversely, in the Eastern centers (AE and PE), nurses more frequently assigned level 2 based on high-risk symptoms than danger-zone vital signs.

A key translational question is whether algorithmic ESI scores could serve as clinical decision support to reduce disparities while preserving patient flow. To probe this, we estimated the impact on ED length of stay (LOS) if algorithmic ESI scores were used in place of nurse-assigned triage scores. We used an accelerated failure time model to estimate the expected change in ED LOS under replacement of nurse-assigned with algorithmic scores, evaluated at triage. At sites AW, AE, PW, and PE, algorithmic ESI would change the proportion of level-2 assignments by 75.7%, -0.1%, 30.5%, and 44.3%, and change the proportion of level-3 assignments by -27.3%, 0.1%, -16.9%, and -23.1%, respectively. Replacing nurse-assigned scores with algorithmic scores was estimated to increase mean ED LOS by 2.0% [2.0–2.1], 1.0% [0.9–1.0], 3.4% [3.4–3.5], and 4.6% [4.5–4.7] at sites AW, AE, PW, and PE, respectively. In AW, where time to admit/discharge decision is available, the estimated change in time to disposition was negligible (-0.1% [-0.1–0.0]). Given the high prevalence of level-3 encounters, a large relative increase in level-2 assignments can be partially offset by a small relative decrease in level-3 assignments. In practice, an ESI algorithm would be decision support rather than a replacement for clinician judgment, and these results suggest potential to reduce disparities with modest or negligible impact on ED throughput.

In summary, we observed significant ethnoracial disparities in triage assignment across four diverse emergency departments, with under-prioritization of minoritized patients relative to Non-Hispanic White patients across centers. These disparities persisted after adjustment for clinical, demographic, and hospital factors available at triage. Notably, disparities were most pronounced among encounters assessed as lower urgency by the ESI algorithm. These findings indicate that disparities are concentrated in discretionary triage decisions where clinicians may be more willing to (differentially) extend the benefit of the doubt, particularly for patients assessed as lower risk by standardized criteria.

Beyond documenting disparities, these findings have important implications for emergency care practice and quality improvement. Our results suggest that the ESI framework, while standardized in principle, is operationalized in ways that allow subjective judgment to differentially influence triage decisions at key decision boundaries. Algorithmic or rules-based decision support that explicitly encodes ESI criteria could therefore serve as a tool to promote consistency in triage assignment, particularly for patients whose presentations fall near acuity thresholds.

Such tools could be integrated into triage workflows as decision aids rather than replacements for clinical judgment, and may inform updates to triage training, audit processes, and quality assurance programs by identifying systematic deviations from guideline-based criteria. More broadly, our findings highlight the need for triage systems and clinical practice guidelines to be evaluated not only for overall accuracy and efficiency, but also for their equity impacts in real-world implementation. Careful design, monitoring, and governance of decision support tools will be essential to ensure that efforts to standardize triage reduce—rather than entrench—existing disparities at the point of first contact in emergency departments.

2 Methods

Here we describe ESI algorithm development, the causal inference approach to estimating disparities in triage assignment, and data preparation for the study.

2.1 ESI Algorithm Development

2.1.1 High-risk patient identification

According to the ESI handbook [8], level-2 criteria include conditions that may rapidly deteriorate or require time-sensitive treatment (Fig. 1A). To computationally replicate this, we extracted 104 high-risk keywords from the ESI handbook and matched them to ED chief complaints (Fig. 1B).

2.1.2 Danger zone vitals identification

When high-risk symptoms are absent but multiple resources are anticipated, ESI next considers vital signs (Fig. 1A). This assessment includes heart rate, respiratory rate, and oxygen saturation. If any

281 vital sign exceeds the danger-zone threshold and multiple resources are anticipated, ESI recommends
282 escalation to level 2 [8].

282 To implement this component, we stratified patients into age groups and compared triage vital signs
283 with age-specific danger-zone thresholds. If any of the three vital signs exceeded threshold, the algorithm
284 assigned level 2. Recent versions of the ESI handbook introduce a “consider” factor [8], allowing clinician
285 discretion when danger-zone vital signs are present, whereas earlier versions did not [7]. We followed the
286 original ESI definition, in which any danger-zone vital sign results in automatic assignment to level 2.
287 We further examine this in Fig. S1.

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289 **2.2 Statistical Analysis**

290 We used causal inference methods to estimate the association between patient race/ethnicity and the
291 odds of receiving an emergency (ESI 2) nurse triage assignment. We approximated the causal effect
292 by matching encounters on clinical presentation and contextual factors before estimating adjusted odds
293 ratios. The approach is described below.

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295 **2.2.1 Exposure of interest and outcome measure**

296 The primary exposure was patient race/ethnicity, categorized as Hispanic, Non-Hispanic Black, Asian,
297 and Other. Encounters with race/ethnicity recorded as “Unknown” were excluded (3.8% on average
298 across datasets) due to uncertainty and potential misclassification. The primary outcome was assignment
300 to nurse-assigned ESI level 2 at triage.

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302 **2.2.2 Adjustment variables**

303 We adjusted for variables available at triage and, where available, diagnoses recorded during the visit
304 to support clinically meaningful matching. All datasets included sex, age, arrival mode, number of prior
305 visits (with and without admission), comorbidity index, triage vital signs (heart rate, respiratory rate,
306 oxygen saturation), and chief complaint. PE and PW additionally included preferred language, social
307 deprivation index, miles traveled, state of origin, number of patients at arrival, and weight. Temporal
308 variables (year and time of arrival) were available for PE and PW, and insurance information was
309 available for PE, PW, and AW.
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312 **2.3 Odds ratio calculation**

313 To assess disparities in ESI level assignment, we performed propensity score matching and estimated
314 adjusted odds ratios [17], using Non-Hispanic White patients as the reference group because it was
315 the largest group overall. For each comparison, analyses were restricted to encounters from the focal
316 ethnoracial group and the reference group. Propensity scores were estimated using logistic regression with
317 ridge regularization, incorporating covariates described in Section 2.2.2. Matching was performed using a
318 ball-tree nearest-neighbors algorithm [18], with calipers of 10% and 20% of the standard deviation of fitted
319 propensity scores. This approach achieved covariate balance across groups, with absolute standardized
320 mean differences ≤ 0.1 for all covariates [17].

321 Odds ratios were computed in matched samples using McNemar’s test with Bonferroni correction for
322 multiple comparisons following 1:1 nearest-neighbor matching. This test assumes independence between
323 matched pairs and conditional independence of outcomes within pairs given the matching variables,
324 assumptions that are reasonable given the encounter-level analysis and strict matching criteria. Differences
325 across algorithmic triage strata within an ethnoracial group were assessed using a z-test, which
326 assumes approximate normality of the log-odds ratio estimates and independent variance estimates across
327 strata. Given the large sample sizes within strata, these normal approximation and variance assumptions
328 are expected to hold.
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331 **2.4 Dataset Preparation**

332 Each dataset was filtered for quality control (see Table S2). Visit records were discarded if any of the
333 following criteria were met: unknown sex (i.e. sex recorded as U or X); missing demographic information;
334 missing patient identifier; disposition other than admission or discharge (e.g. death, left without being
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seen, left against medical advice), or missing disposition with no associated vitals (suggesting departure before triage); missing chief complaint or primary visit diagnosis for datasets where these were recorded separately (suggesting data loss rather than inability to report a complaint); implausibly long visit length in the context of the dataset (generally \geq two weeks), suggesting a recording error; irreconcilable timestamps (e.g. departure time earlier than arrival time).

Variables were processed into categories as described in Table S3. We aimed for consistency across datasets but were constrained by site-specific recording practices. For example, PE recorded both sex and gender, PW and AE recorded only sex, and AW recorded only gender, which was not defined and was assumed to reflect provider-recorded sex. Race/ethnicity recording also differed; notably, AE defined 'Hispanic', 'White', and 'Black' as mutually exclusive categories, whereas other sites recorded Hispanic ethnicity separately from race. We harmonized categories as Hispanic, Non-Hispanic Black, Non-Hispanic Asian (denoted 'Asian'), Non-Hispanic White, Non-Hispanic Other (denoted 'Other'), and 'Unknown'.

Temporal variables (e.g. month, year, crowding) were unavailable for adult datasets, which obscured visit dates for deidentification. In AW, age was shifted by up to two years (all patients were ≥ 18 years, so this shift does not affect ESI algorithm assignments). Both adult datasets truncated ages above 90 at first visit; because such patients were rare, we coarsened older ages into an '80+' group.

Where available, socio-economic and geographic measures (e.g. miles traveled) were divided into dataset-specific quartiles. Socio-economic deprivation scores were obtained from the Robert Graham Center database (2019; most recent available) [19]. This resource assigns a score from 1 (least deprived) to 100 (most deprived) to each U.S. zip code. *Distance traveled to the hospital* was computed assuming travel from the patient's home address.

Chief complaints were grouped using adult and pediatric schemas from [20] and [21], respectively, with site-specific additions where needed to capture common reasons for visit (e.g. shingles for AW; see preprocessing code for details). Primary diagnoses were transformed into binary indicators corresponding to Charlson Comorbidity Index categories for adult datasets (using the R package *comorbidity*) and the Pediatric Comorbidity Index [22] for pediatric datasets. Where available, prior diagnoses (comorbidities) were encoded similarly (e.g. prior diabetes, congestive heart failure, renal disease, cancer). For AE, where prior diagnoses were unavailable, we extracted therapeutic medication classes at the time of visit as proxies for chronic conditions, yielding 85 binary indicators (e.g. thyroid therapy).

Supplementary information. Code supporting this analysis is available at <https://github.com/cavalab/ESI>. The repository includes scripts for dataset preparation and analysis. Supplementary materials include additional cohort descriptions, analyses of the ESI algorithm, and tables documenting preprocessing decisions.

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References

- [1] Institute of Medicine of the National Academies. Hospital-Based Emergency Care: At the Breaking Point. Washington, D.C.: National Academies Press; 2007.
- [2] Rabin E, Kocher K, McClelland M, Pines J, Hwang U, Rathlev N, et al. Solutions To Emergency Department 'Boarding' And Crowding Are Underused And May Need To Be Legislated. *Health Affairs*. 2012 Aug;31(8):1757–1766. <https://doi.org/10.1377/hlthaff.2011.0786>.
- [3] Bees J. Emergency Departments Are Overcrowded and Understaffed. *NEJM Catalyst*. 2022 Jan;3(2). <https://doi.org/10.1056/CAT.22.0011>.
- [4] Hsia RY, Zagorov S, Sarkar N, Savides MT, Feldmeier M, Addo N. Patterns in Patient Encounters and Emergency Department Capacity in California, 2011-2021. *JAMA Network Open*. 2023 Jun;6(6):e2319438. <https://doi.org/10.1001/jamanetworkopen.2023.19438>.
- [5] Cairns C, Kang k. National Hospital Ambulatory Medical Care Survey: 2022 Emergency Department Summary Tables; 2022.

[6] Sun BC, Hsia RY, Weiss RE, Zingmond D, Liang LJ, Han W, et al. Effect of Emergency Department Crowding on Outcomes of Admitted Patients. *Annals of Emergency Medicine*. 2013 Jun;61(6):605–611.e6. <https://doi.org/10.1016/j.annemergmed.2012.10.026>.

[7] Wuerz RC, Milne LW, Eitel DR, Travers D, Gilboy N. Reliability and Validity of a New Five-level Triage Instrument. *Academic Emergency Medicine*. 2000;7(3):236–242. <https://doi.org/https://doi.org/10.1111/j.1553-2712.2000.tb01066.x>. <https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1553-2712.2000.tb01066.x>.

[8] Wolf L, Ceci K, McCallum D, Brecher D. *Emergency Severity Index Handbook Fifth Edition*. Emergency Nurses Association; 2023.

[9] Jordi K, Grossmann F, Gaddis GM, Cignacco E, Denhaerynck K, Schwendimann R, et al. Nurses' Accuracy and Self-Perceived Ability Using the Emergency Severity Index Triage Tool: A Cross-Sectional Study in Four Swiss Hospitals. *Scandinavian Journal of Trauma, Resuscitation and Emergency Medicine*. 2015 Aug;23(1):62. <https://doi.org/10.1186/s13049-015-0142-y>.

[10] Alpert EA, Lipsky AM, Hertz D, Rieck J, Or J. Simulated Evaluation of Two Triage Scales in an Emergency Department in Israel. *European Journal of Emergency Medicine*. 2013 Dec;20(6):431. <https://doi.org/10.1097/MEJ.0b013e32835e2b42>.

[11] Aysola J, Clapp JT, Sullivan P, Brennan PJ, Higginbotham EJ, Kearney MD, et al. Understanding Contributors to Racial/Ethnic Disparities in Emergency Department Throughput Times: a Sequential Mixed Methods Analysis. *Journal of general internal medicine*. 2022;37:341–350. <https://doi.org/10.1007/s11606-021-07028-5>.

[12] Schrader CD, Lewis LM. Racial disparity in Emergency Department triage. *Journal of Emergency Medicine*. 2013;44:511–518. <https://doi.org/10.1016/j.jemermed.2012.05.010>.

[13] Zhang X, Carabello M, Hill T, Bell SA, Stephenson R, Mahajan P. Trends of Racial/Ethnic Differences in Emergency Department Care Outcomes Among Adults in the United States From 2005 to 2016. *Frontiers in Medicine*. 2020;Volume 7 - 2020. <https://doi.org/10.3389/fmed.2020.00300>.

[14] Joseph JW, Landry AM, Kennedy M, Baymon DE, Bakhman AK, Elhadad N, et al. Association of Race and Ethnicity With Triage Emergency Severity Index Scores and Total Visit Work Relative Value Units for Emergency Department Patients. *JAMA Network Open*. 2022;9(9):e2231769–e2231769. <https://doi.org/10.1001/jamanetworkopen.2022.31769>.

[15] Sax DR, Warton EM, Mark DG, Vinson DR, Kene MV, Ballard DW, et al. Evaluation of Version 4 of the Emergency Severity Index in US Emergency Departments for the Rate of Mistriage. *JAMA Network Open*. 2023;6(3):e233404–e233404. <https://doi.org/10.1001/jamanetworkopen.2023.3404>.

[16] Wolf L, Delao A, Jodelka FM, Simon C. Determining Emergency Severity Index Acuity: Key Triage Elements Identified by Emergency Nurses. *Journal of Emergency Nursing*. 2025;51(3):472–479. <https://doi.org/https://doi.org/10.1016/j.jen.2024.11.003>.

[17] Austin PC. An Introduction to Propensity Score Methods for Reducing the Effects of Confounding in Observational Studies. *Multivariate behavioral research*. 2011;5:46:399–424. <https://doi.org/10.1080/00273171.2011.568786>.

[18] Geldof T, Popovic D, Van Damme N, Huys I, Van Dyck W. Nearest Neighbour Propensity Score Matching and Bootstrapping for Estimating Binary Patient Response in Oncology: A Monte Carlo Simulation. *Scientific Reports*. 2020 Jan;10(1). <https://doi.org/https://doi.org/10.1038/s41598-020-57799-w>.

[19] Robert Graham Center - Policy Studies in Family Medicine & Primary Care.: Social deprivation index (SDI). Available from: <https://www.graham-center.org/maps-data-tools/social-deprivation-index.html>. 449
450

[20] Arya R, Wei G, McCoy JV, Crane J, Ohman-Strickland P, Eisenstein RM. Decreasing Length of Stay in the Emergency Department With a Split Emergency Severity Index 3 Patient Flow Model. Academic Emergency Medicine. 2013 11;20:1171–1179. <https://doi.org/10.1111/acem.12249>. 451
452
453
454

[21] Gorelick MH, Alpern ER, Alessandrini EA. A System for Grouping Presenting Complaints: The Pediatric Emergency Reason for Visit Clusters. Academic Emergency Medicine. 2005 8;12:723–731. <https://doi.org/10.1197/j.aem.2005.03.530>. 455
456
457
458

[22] Sun JW, Bourgeois FT, Haneuse S, Hernández-Díaz S, Landon JE, Bateman BT, et al. Development and Validation of a Pediatric Comorbidity Index. American Journal of Epidemiology. 2021 5;190:918–927. <https://doi.org/10.1093/aje/kwaa244>. 459
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