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Assessing the Impact of Waiting Time on Triage Color Code Assignment and One-Year Mortality in the Emergency Department: A Causal Mediation Analysis

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ABSTRACT

Background and Aims: Emergency Department (ED) overcrowding and delays in care affect patient outcomes. While triage systems prioritize care based on urgency, the role of waiting time in mediating the relationship between triage color codes and 1-year mortality remains unclear. This study investigates this mediation effect to improve triage protocols and patient outcomes.

Methods: A retrospective cohort study was conducted using data from the Fondazione Policlinico Universitario Agostino Gemelli IRCCS ED (2014–2018). The sample included patients assigned green and yellow triage codes, excluding red and white ones. The outcome was 1-year mortality; the mediator was waiting time, defined as the delay between triage assignment and medical evaluation. Causal mediation analysis estimated direct, indirect, and total effects, with sensitivity analyses assessing robustness to unmeasured confounding.

Results: Among 56,284 observations, older patients and yellow-coded individuals showed higher 1-year mortality. Waiting time did not significantly mediate the relationship between triage code and mortality (ACME OR: 1.001, 95% CI: 0.999–1.002). Triage code, however, had a direct significant effect on mortality (ADE OR: 1.01, 95% CI: 1.004–1.007). Waiting time mediated a small proportion of the effect (3.4%–13.9%). Sensitivity analyses indicated the mediation effect was sensitive to unmeasured confounding.

Conclusions: Triage color code strongly predicts 1-year mortality, independent of waiting time within standard thresholds. For lower-acuity cases, reducing waiting time further may not improve long-term outcomes. Future research should validate these findings across multicenter settings and explore Italy's updated five-color triage system to optimize care delivery.

1 | Introduction

As the primary line of defense in a healthcare system, the emergency department (ED) addresses both disaster situations and everyday urgent needs [1]. Known for its efficiency in delivering critical, life-saving treatment, it also serves as a key provider of ambulatory services [2]. However, a significant portion of visits to the ED involves non-urgent conditions, contributing to inflated healthcare costs, unnecessary diagnostic tests, and potentially avoidable treatments [3]. These challenges are compounded by the increasing demand for emergency services, which often exceeds the available resources, leading to overcrowding—a persistent concern in EDs worldwide [4, 5]. Although a precise, universally accepted definition does not exist, overcrowding typically occurs when the number of patients waiting for care exceeds the ED's available space and staffing capabilities, thereby disrupting its normal functioning [6]. EDs are critical points of care in healthcare systems, where timely and accurate clinical decisions can significantly affect patient outcomes [7].

Overcrowding raised concerns regarding patient safety and mortality, particularly related to waiting times for evaluation and treatment [8]. Treatment delay is defined as the time between the onset of symptoms and the initiation of medical intervention [9]. Such delays often adversely impact patient outcomes in the ED, leading to poorer prognoses [9]. For instance, failing to administer antibiotics within 3 h [10] or thrombolysis within 60 min [11] can significantly affect the quality of care and worsen patient progression. By systematically assessing the urgency of each patient's condition, triage ensures that those with the most critical needs receive prompt attention, while less urgent cases are prioritized accordingly [12].

This process helps manage patient flow effectively, reduces wait times for urgent cases, and improves overall care quality. Proper triage is essential for optimizing resource allocation, enhancing patient outcomes, and minimizing delays in treatment [13]. Triage errors fall into two categories: under triage and over triage. The former happens when a patient's condition is not given the urgency it requires, causing them to receive insufficient care, which might aggravate their health problems [14]. The latter, on the other hand, involves providing more immediate care than necessary to patients with less critical conditions, leading to the inefficient use of resources and possibly exposing patients to unnecessary and potentially harmful procedures [15].

Emerging evidence suggests that initial triage decisions may also have significant long-term implications, potentially shaping overall patient trajectories: in particular, under triage can have a substantial impact on long-term outcomes, as delays in appropriate diagnosis and treatment may exacerbate underlying conditions, complicate recovery, and ultimately increase mortality risk [16]. Additionally, prolonged waiting times, especially for patients assigned lower acuity codes, may further compromise outcomes by delaying essential care, exacerbating pre-existing comorbidities, and increasing the risk of adverse events [17].

In the ED, triage is one of the most vital and complex responsibilities assigned to nurses [18]. The role requires quick decision-making, strong communication, critical thinking, and the ability to handle multiple tasks at once [19]. Triage nurses are expected to assess and prioritize patients within minutes [20], and errors in these decisions can have life-or-death consequences. While triage nurses must be highly skilled in making these urgent decisions, their capacity to process information is challenged by growing patient numbers, increasing severity of cases, limited resources, and the unpredictable nature of the ED [21]. This combination of factors heightens the pressure on triage clinicians, making it increasingly difficult to ensure accurate and effective patient assessments [22].

Despite the widespread recognition of these challenges [21], the mediating role of triage categorization in the relationship between ED waiting times and patient mortality has been underexplored. Understanding how triage assignment interacts with waiting time to influence 1-year mortality is crucial for optimizing triage protocols and improving patient outcomes.

The aim of this study is to analyze the mediation effects between the assigned triage color code and waiting times for evaluation in the ED, and how these factors collectively influence 1-year mortality.

2 | Materials and Methods

This study was approved by the Ethics Committee of the FPG (Prot. 0025817/22, ID 5121, approved on 28th July 2022). For all eligible patients, informed consent was obtained following a detailed explanation of the study. Anonymity and protection of personal data was ensured, while also guaranteeing participants the right to decline or withdraw from the study at any stage. The research adhered to the principles of good clinical practice, the Declaration of Helsinki, and all relevant regulations.

This study adhered to the "A Guideline for Reporting Mediation Analyses (AGReMA) statement", to ensure comprehensive and transparent reporting of the causal mediation analysis.

2.1 | Study Design and Source of Data

This retrospective cohort study was conducted using information retrieved from the administrative data set of the ED at the Fondazione Policlinico Universitario Agostino Gemelli IRCCS (FPG) in Rome, Italy. The FPG is the largest hospital in Italy and its ED handles over 68,000 cases annually, predominantly addressing the healthcare needs of the Lazio region's population. Our data set spans the period from 2013 to 2023; however, the analysis was limited to the years 2014–2018 for several reasons. Firstly, records from 2020 onwards were excluded due to the onset of the COVID-19 pandemic. Additionally, data from 2019 were omitted from the baseline analysis but adopted to construct our indicators, as it is necessary to observe visits to the ED within 1 year of the last access. Similarly, the 2014 data were used solely to generate control variables related to previous ED visits.

2.2 | Target Population and Sample Size

Sample size was obtained by a convenience sampling. Participants were consecutively recruited from individuals who presented to the ED and were subsequently admitted. Each patient was assigned a unique triage code (i.e., white, green, yellow, or red) upon arrival, which corresponded to their clinical urgency. The patients were seeking evaluations for varied clinical presentations, including trauma or burn and other symptoms or disorders. Those diagnosed, at the triage stage, with time sensitive severe diseases coded as red code (e.g., myocardial infarction, stroke, sepsis) were excluded.

Furthermore, only nurses, who triaged at least ten individuals per month, resulting in a sample of 59 nurses, observed between 2015 and 2018, were included.

2.3 | Study Variables and Definitions

The outcome variable (Y) for this study was the 365-day mortality rate, defined as a binary variable, with a value of 1 signifying that the patient passed away within a year after being released from the ED and 0 indicating that they survived past this time.

The treatment or exposure variable (T), investigated in relation to mortality, was the triage color code assigned during triage in the ED. In Italy, up until 2019, four triage color codes were used: red, yellow, green, and white. Each color code was associated with a specific severity of illness and a corresponding waiting time. The red code, assigned to patients with alterations in vital functions, allowed immediate access to the ED. The yellow code was designated for patients at risk of alterations in vital functions and was associated with a waiting time of up to 60 min for entry into the ED. The green code, for patients who were not at risk and in stable condition requiring only simple therapeutic interventions, had a maximum waiting time of 120 min. Finally, the white code was assigned to patients not at risk of life-threatening conditions and who did not require hospital intervention, and thus incurring a health service fee and facing a maximum waiting time of 240 min [23]. For the purposes of the analysis, the red codes were excluded since their waiting time is zero, indicating emergencies that necessitate immediate attention. White codes were dropped due to the extremely low number of observations within the data set.

The mediator variable (M) was the waiting time defined as the difference between the time of triage color code assignment and the time of acceptance (i.e., entry and evaluation) in the ED. It was calculated in hours for each patient.

Additional covariates, as well as potential confounders, assessed in this study for each patient included age, gender, day of the week and month of ED admission. Furthermore, characteristics of the ED and nursing staff were considered, such as the number of daily ED admissions (i.e., overcrowding), the experience of the nurses (i.e., number of visits per month), and the presence of night shifts.

2.4 | Effects of Interest

In the present study, the following effects of interest were investigated: (i) the total effect (TE) of triage color code on 1-year mortality, which encompasses both direct and indirect pathways; (ii) the direct effect (ADE) of triage color code on mortality, independent of waiting time; and (iii) the indirect effect (ACME), also known as the mediation effect, which captures the impact of triage color code on mortality through waiting time. Additionally, (iv) the proportion mediated (PM) was assessed, representing the proportion of the total effect explained by the mediator. Further, (v) the controlled direct effect (CDE), evaluating the impact of triage color code on mortality with waiting time held constant, (vi) the natural direct effect (NDE), and (vii) the natural indirect effect (NIE), which allow the mediator to vary naturally under different conditions were also considered.

2.5 | Causal Model and Assumptions

The validity of the causal mediation analysis is strictly related to the key assumptions outlined before the conduction of the analysis. Particularly, consistency was assumed so that outcomes and mediators, for each individual, are consistent with their observed values under the actual treatment received.

Furthermore, also positivity was considered to ensure that every combination of covariates has a non-zero probability of receiving each treatment level and each mediator value. This is crucial for guaranteeing sufficient variability to estimate the effects accurately.

No unmeasured confounding was assumed, meaning that all variables that could potentially confound the relationships between the triage color code (i.e., treatment), waiting time in the ED (i.e., mediator), and 1-year mortality rate (i.e., outcome) were measured and included in the model. In doing so, bias from unmeasured variables may be eliminated.

The sequential ignorability assumption was also applied, which posits that the assignment of the triage color code is independent of the potential mediator (i.e., waiting time) and potential outcomes (i.e., 1-year mortality), given the observed covariates. Additionally, the mediator is assumed to be independent of the potential outcomes, given the treatment and the observed covariates.

To further elucidate the assumed causal relationships, a causal directed acyclic graph was set up to visually represent the pathways and dependencies among the variables included in the model (Figure 1).

2.6 | Statistical Analysis

Initial descriptive statistics were performed on the study population and populational subgroups based on 365-day mortality. Multivariate regression analyses were performed to assess potential confounders of both the mediator and the outcome.

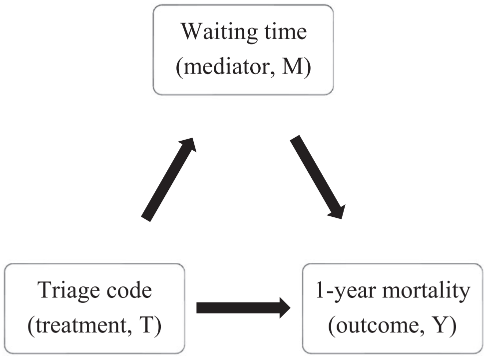

FIGURE 1 | Causal directed acyclic graph illustrating the assumed relationships between triage color code (i.e., treatment), waiting time in the ED (i.e., mediator), 1-year mortality rate (i.e., outcome). The arrows represent the assumed causal directions.

Specifically, the mediator was regressed on the treatment and various covariates, while the outcome was regressed on the treatment, mediator, and the same set of covariates. Variables that significantly predicted the mediator and the outcome were identified as potential confounders. For both models, variance was estimated using robust standard errors to ensure validity under potential heteroscedasticity [24, 25].

Conventional mediation analysis, developed by Baron and Kenny in 1986 [26] and further elaborated by MacKinnon in 2008 [27], is based on the principles of linear structural equation modeling (SEM).

In causal mediation analysis, the causal mediation effect is defined, in the potential outcome framework, as the difference between the participant's observed outcome and a counterfactual outcome, where the treatment status remains identical, but the mediator value is equal to what it would be under the alternative treatment status,

$$\delta_i(t) = Y_i(t, M_i(1)) - Y_i(t, M_i(0))$$

where $t = 0, 1$.

To compute causal mediation effects, two regression equations are first specified and fitted. Specifically, a logit model was employed for the outcome while a linear model for the mediator:

$$P(Y^{(i)} = 1|T, M, X) = \frac{1}{1 + e^{(-(\beta_0 + \beta_1 T_i + \beta_2 M_i + \beta_3 T_i M_i + \beta_4 X_i + \varepsilon_Y))}}$$

$$M_i = \alpha_0 + \alpha_1 T_i + \alpha_2 X_i + \varepsilon_M$$

where Y is the binary outcome, T is the treatment, M is the mediator, and X is a vector of covariates. In the outcome model, β_0 is the intercept, β_1 is the coefficient for the treatment, β_2 is the coefficient for the mediator, β_3 is the coefficient for the interaction between the treatment and the mediator, β_4 is a matrix of coefficients for the covariates, and ε_Y is the error term. The outcome model regressed 1-year mortality (Y) on T, M, their interaction ($T \times M$), and the covariates using a binomial generalized linear model with a logit link, with heteroskedasticity-robust standard errors. In the mediator model, α_0 is the intercept, α_1 is the coefficient for the treatment, α_2 is a matrix of coefficients for the covariates, and ε_M is the error term [28]. The mediator model regressed waiting time (M) on triage color code (T) and covariates using linear regression also with heteroskedasticity-robust standard errors.

Once mediation and direct effects have been estimated, sensitivity analyses were conducted to explore how robust the findings are to the mediator–outcome ignorability assumption. Therefore, the Rho parameter (r) was assessed to measure the degree of correlation, between the error terms of the mediator and the outcome models, which could point out the presence of unmeasured confounding that might bias the estimated mediation effects.

A r equals to zero implies that there is no unmeasured confounding affecting the mediation analysis, and the assumptions of the mediation analysis hold true. Conversely, a non-zero ρ indicates the presence of some correlation between the error terms. Regarding the magnitude and direction, a positive ρ suggests that unmeasured factors are positively correlated with both the mediator and the outcome, leading to overestimation of the mediation effects. A negative ρ outlines the diametrically opposite effect.

The results of the mediation analysis are usually estimated in terms of the original scale of the outcome variable [29] and the confidence intervals generated using a quasi-Bayesian Monte Carlo method with 1000 draws. This approach involves drawing many simulated samples from the posterior distribution of the estimated parameters. By repeatedly sampling from this distribution, the method approximates the distribution of the mediation effects allowing for the construction of confidence intervals, thus capturing the uncertainty in the mediation estimates. Nonetheless, to ease the interpretation of the findings, results were expressed and reported as odds ratios (OR) along with their respective 95% confidence intervals (CI), calculated according with the method suggested by Katz et al. [30]. Missing data were handled using a complete-case approach.

All statistical analyses were performed using R (R Foundation for Statistical Computing, Vienna, Austria) version 4.4.1 and significance was set at 5% ($p < 0.05$). The mediation analysis was conducted adopting the *mediation* package [31, 32].

3 | Results

3.1 | Descriptive Statistics

A total of 60,652 recordings were collected from the main data set, and a total of 56,284 observations were recorded for each individual following a preliminary analysis of the same data set, more specifically by deleting missing data regarding variables considered in this study. The 365-day mortality has been assessed and is reported stratified by triage code status and other variables in Table 1.

TABLE 1 | Demographic and ED characteristics for individuals dying within 1 year and those not.

	Individuals died within 1 year		Individuals alive within 1 year	
	Green	Yellow	Green	Yellow
Demographic characteristics (% col)				
Sex				
Male (%)	24 (40,00)	113 (47,08)	22,723 (54,24)	7,249 (51,42)
Female (%)	36 (60,00)	127 (52,92)	19,171 (45.76)	6,848 (48,58)
Age, years (mean)	77,93	83,58	35,31	50,54
Mean age for dead or alive within 1 year	82,45		39,14	
Age class				
0–14 (%)	0 (0)	0 (0)	11,077 (26,44)	2,346 (16,64)
15–34 (%)	0 (0)	1 (0,42)	10,685 (25,50)	2,408 (17,08)
35–50 (%)	6 (10.00)	2 (0,83)	8,127 (19,40)	1,876 (13,31)
51–64 (%)	2 (3,33)	12 (5,00)	5,978 (14,27)	1,797 (12,75)
> 65 (%)	52 (86,67)	225 (93,75)	6,027 (14,39)	5,670 (40,22)
total	60	240	41,894	14,097
ED characteristics (% col)				
Waiting time (mean, hours)	1,13	0,44	1,12	0,40
Mean waiting time for dead or alive within 1 year	0,57		0,93	
Mean Daily Hospital Admission	275,92			

Regarding gender, there is a noticeable disparity in 365-day mortality, with fewer males dying within 1 year compared to females (137 *vs.* 163, respectively). Nevertheless, the number of males surviving beyond 1 year is greater compared to females (29,972 *vs.* 26,019, respectively). The 365-day mortality rate is notably higher among yellow-coded females.

The difference in 365-day mortality is also observable concerning the average age and age groups: individuals who died within 1 year are, on average, older compared to those who survived (82,45 years *vs.* 39,14 years, respectively). Specifically, among both those who died within 1 year and those who did not, the majority are yellow coded individuals. When categorized by age, the distribution of deaths within 1 year is as follows: 0 subjects aged 0–14 years; 1 individual aged 15–34 years; eight individuals aged 35–50 years; 14 individuals aged 51–64 years; and 277 individuals aged 65 years or older. In contrast, among those surviving beyond 1 year, there are 13,423 individuals aged 0–14 years; 13,093 individuals aged 15–34 years; 10,003 individuals aged 35–50 years; 7,775 individuals aged 51–64 years; and 11,697 individuals aged 65 years or older. Among those dying within 1 year, the largest segment consists of individuals aged 65 years or older. In contrast, among those surviving beyond 1 year the majority comprises individuals aged 0–14 years.

Concerning ED descriptive characteristics, mean waiting time (calculated as the mean time between the allocation of the triage code and the medical visit within the ED) for those who died within 1 year was lower than for those who survived beyond 365 days (0,57 h *vs.* 0,93 h, respectively). More specifically, among those who died within 1 year, individuals with yellow code status waited a mean time of 0,44 h, compared to 1,13 h for those with green code status; meanwhile, those surviving beyond 1 year waited a mean time of 0,40 h if they were flagged yellow at the triage, or 1,12 if they had a green flag. The average daily hospital admission was 275,92 individuals.

3.2 | Causal Mediation Analysis

Causal mediation analysis showed that there is no strong evidence that waiting time significantly mediates the relationship between the triage color code and 1-year mortality. The estimates for ACME are quite small and not statistically significant (OR 1.001, 95% CI: 0.999–1.002), implying a minimal impact of the mediator on the outcome.

Conversely, triage color code had a direct significant effect on 1-year mortality, independent of waiting time. Although small, estimates for ADE are highly statistically significant with an increase of one-point percent in the probability of 1-year mortality when increasing the severity of the clinical condition (OR 1.01, 95% CI: 1.004–1.007).

Besides, TE estimates are statistically significant (OR 1.006, 95% CI: 1.004–1.008), confirming the robust association between triage color code and 1-year mortality.

Analyzing the PM, waiting time mediated roughly the 3.4% (95% CI: 1.2%–12%) to 13.9% (95% CI: 5.8%–38%) of the effect of the triage color code on mortality in control and treated groups, respectively.

Sensitivity analyses indicated that ACME are small or close to zero under the assumption of no unobserved confounding. Notwithstanding, the estimated ACME becomes sensitive to positive unobserved confounding as ρ increases beyond 0.3. The presence of unmeasured factors that are positively correlated with both waiting time and mortality implies that ACME could be more substantial than the initial estimates suggest (Fig. S1). Under the alternative scenario, the scenario does not change since as ρ increases ACME weakens and may become neutral or slightly positive under high levels of positive unobserved confounding (Fig. S2). Changing the sensitivity parameter to R^2, the sensitivity analysis shows that ACME is relatively robust to unmeasured confounding, even though its magnitude decreases as more variance in either the mediator or the outcome is explained by unobserved factors. Unobserved confounders affecting the waiting time have a larger influence on the ACME than those influencing the 1-year mortality (Fig. S3). Even in the alternative scenario, the ACME is more sensitive to confounders affecting waiting time than to those affecting mortality. The computed ACME is positive and small when no unobserved confounding is assumed (~0.008). However, as more variance in the mediator or outcome is explained by unmeasured confounders, the mediation effect decreases (Fig. S4). Sensitivity plots are presented in the Supporting Information.

4 | Discussion

The triage color code has a significant direct effect on 1-year mortality, meaning that the assignment of a triage color has a direct association with the likelihood of mortality, irrespective of a waiting time lower than 6 h which does not mediate the relationship between the other two variables in any meaningful way.

Other studies have similarly investigated the effect of waiting times on mortality in ED. Jones et al. [33]. investigated the association between ED wait times and all-cause 30-day mortality rate. The largest shift in the 30-day standardized mortality ratio was an 8% rise, observed in the patient cohort that waited over six to 8 h in the ED from arrival. These results are in line with those of our earlier observations, which showed no significant indirect effect of waiting time on 1-year mortality. Our results seem to be consistent with other research [34] which found that patients who spent more than 8 h in the ED had a notably higher risk of adverse outcomes compared to those with shorter waiting times. In addition, our findings are further supported by Plunkett et al. [35], who demonstrated that increasing wait times, particularly beyond 6 h, significantly increased mortality rates for emergency medical admissions. Byrne et al. [36], similarly, highlighted the link between waiting times and mortality, finding a 6.6% mortality rate for patients waiting less than 4 h.

Among the studies examining the relationship between triage color codes and 1-year mortality, Gonçales et al. [37]. employed the Manchester Triage System (MTS) [38]. to prioritize patient access to the ED. The study concluded that the triage system, administered by hospital nurses, served as a reliable predictor of 30-day mortality among ED patients. Specifically, the risk of death was found to be highest for patients assigned a red code, followed by those categorized as orange, with progressively lower mortality risk for patients classified under yellow, green, and blue, respectively.

Another study from Daebes et al. [39]. examining the South African Triage Scale (SATS) [40]. in emergency medical services assessed the relationship between triage color code and 30-day mortality. The findings revealed that patients assigned a red triage code had an increased likelihood of experiencing death within 30 days.

The joint reading of these findings allows for some conceptual main implications.

For lower-acuity patients, further reductions in waiting time below referenced thresholds may not yield to substantial improvements in long-term survival. However, prioritizing timely care for patients with urgent triage codes remains crucial for short-term survival.

Furthermore, the direct effect of triage color code assignment on 1-year mortality underscores the predictive power of triage systems in determining patient outcomes. Improving the accuracy and consistency of these assignments could be critical in enhancing patient care, particularly for those at higher risk of adverse outcomes. To achieve this, a dual approach could be considered: leveraging the expertise of experienced nurses alongside AI-driven decision support tools.

Nurses bring valuable clinical judgment to the triage process, drawing from their experience and contextual understanding of each patient's condition. Nonetheless, human judgment can sometimes be influenced by workload, stress, or environmental factors, potentially leading to variability in triage decisions. By integrating AI-based systems that analyze real-time patient data and historical trends, healthcare facilities can provide nurses with enhanced support in making more consistent and accurate triage decisions [41]. AI tools could assist in identifying subtle clinical signs that might indicate a higher risk of mortality or deterioration, particularly for borderline cases where the urgency may not be immediately clear.

Triage systems worldwide exhibit similar patterns in predicting patient mortality [42–44]. This convergence in predictive accuracy indicates that triage systems, despite geographical and procedural differences, are broadly effective in stratifying patient risk in emergency settings. Such consistency presents an opportunity for cross-system learning, where healthcare facilities can collaboratively refine triage practices by sharing data-driven insights and best practices to improve ED efficiency and patient care outcomes.

Sharing best practices could help standardize triage protocols globally, leading to improved patient outcomes. For instance, hospitals with successful AI-enhanced triage models could share implementation strategies and outcome data with institutions that are developing or refining their triage protocols.

Additionally, cross-system comparisons could highlight specific areas for improvement, such as the optimal integration of triage systems with downstream care processes. Such collaborative approaches can foster a global framework for continuous improvement in triage practices, enabling EDs to manage patient flow more efficiently and reduce mortality rates across diverse healthcare settings.

The present study should be considered in light of its main limitations and strengths. The observed small magnitude of the mediation effect may be partly related to the low number of deaths within the sample, which could reduce the statistical power and impact the overall findings. Nonetheless, the large sample size may enhance the reliability of the results and allow for a nuanced understanding of how triage color codes relate to mortality outcomes over 1 year. Another caveat concerns the mediation effect of waiting time, which was found to be minimal and highly sensitive to unobserved confounding, suggesting that the true mediation effect could be underestimated. Notwithstanding, the use of sensitivity analyses could offer insights into both the direct and indirect effects of waiting time on the studied association. Importantly, the study carefully examines the proportion of the triage effect mediated by waiting time, which is a critical component in understanding ED processes and their potential impact on patient outcomes.

Furthermore, the observational nature of the data limits the ability to draw definitive causal inferences, as confounding variables may not be fully accounted for despite adjustments. Lastly, the generalizability of the findings may be limited to the specific ED context in which the study was conducted, necessitating caution when applying the results to other healthcare settings or populations.

In this study, the pivotal role of waiting time as a mediator in the relationship between ED triage color codes and 1-year mortality is emphasized. Nonetheless, further research is crucial to deepen our comprehension of the underlying mechanisms and may ultimately guide improvements in emergency care delivery. This is particularly pertinent in light of the continuous evolution of triage systems and healthcare policies. In 2019, Italy introduced a revised triage classification system, transitioning from a four-color scheme (i.e., red, yellow, green, and white) to a five-color framework (i.e., red, orange, blue, green, and white). This shift introduces new layers of complexity that future research must address. Specifically, the addition of the orange (urgent but not life-threatening) and blue (urgent but deferrable) categories may alter the patient distribution across urgency levels. From this perspective, it is imperative that future studies investigate how these added categories influence both mediator and outcome variables, particularly regarding mortality risk.

Moreover, although the current findings are informative, the study was conducted at a single center, which may limit the generalizability of the results. Future research should replicate the analysis in a multicenter context to validate these findings across diverse patient populations and healthcare settings, thus improving the accuracy of the findings. This approach would offer a more comprehensive understanding of how waiting times and triage protocols affect patient outcomes across different clinical environments.

5 | Conclusion

Findings confirm that the assigned triage color code serves as a strong predictor of mortality, independent of ED waiting times. This insight highlights the importance of accurate and consistent triage assignments to effectively prioritize high-risk patients. Nonetheless, this process may pose challenges. Variability in triage decisions can arise from differences in staff experience [45, 46], inherent subjectivity in evaluating patient conditions, as well as fluctuating ED demands [47]. Implementing specialized training, continuous assessment, and possibly integrating AI-supported tools may help mitigate these challenges, but resource constraints and technological limitations remain hurdles for many institutions to overcome.

Author Contributions

Mario Cesare Nurchis: methodology, conceptualization, writing – original draft. **Marcello Covino:** validation. **Cosimo Savoia:** methodology, writing – original draft. **Gerardo Altamura:** writing – original draft. **Andrea Cambieri:** validation, writing – review and editing. **Gabriele Giubbini:** validation, writing – review and editing. **Giuseppe Vetrugno:** validation, writing – review and editing. **Manuele Cesare:** validation, writing – review and editing. **Antonello Cocchieri:** validation, writing – review and editing. **Francesco Franceschi:** validation, writing – review and editing. **Walter Ricciardi:** validation. **Gianfranco Damiani:** validation.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request. All authors have read and approved the final version of the manuscript. Dr. Cosimo Savoia had full access to all of the data in this study and takes complete responsibility for the integrity of the data and the accuracy of the data analysis.

Transparency statement

Dr. Mario Cesare Nurchis affirms that this manuscript is an honest, accurate, and transparent account of the study being reported; that no important aspects of the study have been omitted; and that any discrepancies from the study as planned (and, if relevant, registered) have been explained.

References

1. N. Al Nhdi, H. Al Asmari, and A. Al Thobaity, "Investigating Indicators of Waiting Time and Length of Stay in Emergency Departments," *Open Access Emergency Medicine* 13 (2021): 311–318.

2. Medicine I of Hospital-Based Emergency Care: At the Breaking Point [Internet]. The National Academies Press; 2007. https://nap.

nationalacademies.org/catalog/11621/hospital-based-emergency-care-at-the-breaking-point.

3. L. Uscher-Pines, J. Pines, A. Kellermann, E. Gillen, and A. Mehrotra, "Emergency Department Visits for Nonurgent Conditions: Systematic Literature Review," *American Journal of Managed Care* 19, no. 1 (2013): 47–59.

4. M. C. van der Linden, B. E. A. M. Meester, and N. van der Linden, "Emergency Department Crowding Affects Triage Processes," *International Emergency Nursing* 29 (2016): 27–31.

5. M. Sartini, A. Carbone, A. Demartini, et al., "Overcrowding in Emergency Department: Causes, Consequences, and Solutions—A Narrative Review," *Healthcare* 10, no. 9 (2022): 1625.

6. R. Salway, R. Valenzuela, J. Shoenberger, W. Mallon, and A. Viccellio, "Emergency Department (ED) Overcrowding: Evidence-Based Answers to Frequently Asked Questions," *Revista Médica Clínica Las Condes* 28, no. 2 (2017): 213–219.

7. R. A. Rutkowski, E. Scheer, C. Carlson, et al., "A Scoping Review of Work System Elements That Influence Emergency Department Disposition Decision-Making," *Human Factors in Healthcare* 4 (2023): 100059.

8. A. Darraj, A. Hudays, A. Hazazi, A. Hobani, and A. Alghamdi, "The Association Between Emergency Department Overcrowding and Delay in Treatment: A Systematic Review," *Healthcare* 11, no. 3 (2023): 385.

9. I. Beltrán Guzmán, J. Gil Cuesta, M. Trelles, et al., "Delays in Arrival and Treatment in Emergency Departments: Women, Children and Non-Trauma Consultations the Most at Risk in Humanitarian Settings," *PLoS One* 14, no. 3 (2019): e0213362.

10. R. P. Dellinger, M. M. Levy, A. Rhodes, et al., "Surviving Sepsis Campaign: International Guidelines for Management of Severe Sepsis and Septic Shock, 2012," *Intensive Care Medicine* 39, no. 2 (2013): 165–228.

11. W. J. Powers, A. A. Rabinstein, T. Ackerson, et al., "2018 Guidelines for the Early Management of Patients With Acute Ischemic Stroke: A Guideline for Healthcare Professionals From the American Heart Association/American Stroke Association," *Stroke* 49, no. 3 (2018): 158.

12. R. Mostafa and K. El-Atawi, "Strategies to Measure and Improve Emergency Department Performance: A Review," *Cureus* 16 (2024): e52879.

13. B. Adhikari, L. Shrestha, M. Bajracharya, et al., "Triage Practices for Emergency Care Delivery: A Qualitative Study Among Febrile Patients and Healthcare Workers in a Tertiary Care Hospital in Nepal," *BMC Health Services Research* 24, no. 1 (2024): 180.

14. E. Jeppesen, M. Cuevas-Østrem, C. Gram-Knutsen, and O. Uleberg, "Undertriage in Trauma: An Ignored Quality Indicator?," *Scandinavian Journal of Trauma, Resuscitation and Emergency Medicine* 28, no. 1 (2020): 34.

15. T. Huabbangyang, R. Rojsaengroeng, G. Tiyawat, et al., "Associated Factors of Under and Over-Triage Based on The Emergency Severity Index; a Retrospective Cross-Sectional Study," *Archives of Academic Emergency Medicine* 11, no. 1 (2023): e57.

16. K. Staudenmayer, F. Lin, R. Mackersie, D. Spain, and R. Hsia, "Variability in California Triage From 2005 to 2009," *Journal of Trauma and Acute Care Surgery* 76, no. 4 (2014): 1041–1047.

17. S. Kwasnick, D. Luo, M. Bayati, and E. L. Plambeck, "Low-Acuity Patients Delay High-Acuity Patients in the ED," *SSRN Electronic Journal* 1 (2017): 1.

18. M. Ebrahimi, A. Mirhaghi, R. Mazlom, A. Heydari, A. Nassehi, and M. Jafari, "The Role Descriptions of Triage Nurse in Emergency Department: A Delphi Study," *Scientifica* 2016 (2016): 1–6.

19. K. Kennedy, R. Aghababian, L. Gans, and C. Lewis, "Triage: Techniques and Applications in Decisionmaking," *Annals of Emergency Medicine* 28, no. 2 (1996): 136–144, https://doi.org/10.1016/S0196-0644(96)70053-7.

20. A. K. Andersson, M. Omberg, and M. Svedlund, "Triage in the Emergency Department – a Qualitative Study of the Factors Which Nurses Consider When Making Decisions," *Nursing in Critical Care* 11, no. 3 (2006): 136–145.

21. M. AlShatarat, A. Rayan, N. F. Eshah, M. H. Baqeas, M. J. Jaber, and M. ALBashtawy, "Triage Knowledge and Practice and Associated Factors Among Emergency Department Nurses," *SAGE Open Nursing* 8 (2022): 23779608221130588.

22. M. R. Reinhardt, "A Systematic Approach to Evaluation of Performance Deficiencies in ED Triage," *Journal of Emergency Nursing* 43, no. 4 (2017): 329–332.

23. ACCORDO 25 ottobre 2001 - Accordo tra il Ministro della salute, le regioni e le province autonome sul documento di linee-guida sul sistema di emergenza sanitaria concernente: "Triage intraospedaliero (valutazione gravita' all'ingresso) e chirurgia della mano e microchirurgia nel sistema dell'emergenza - urgenza sanitaria". (GU Serie Generale n.285 del 07-12-2001) [Internet]. 2001 [cited 2024 Dec 18]. https://www.gazzettaufficiale.it/eli/id/2001/12/07/01A12203/sg.

24. M. J. Hinich and P. P. Talwar, "A Simple Method for Robust Regression," *Journal of the American Statistical Association* 70, no. 349 (1975): 113–119.

25. R. M. Royall, "Model Robust Confidence Intervals Using Maximum Likelihood Estimators," *International Statistical Review/Revue Internationale de Statistique* 54, no. 2 (1986): 221.

26. R. M. Baron and D. A. Kenny, "The Moderator–Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic, and Statistical Considerations," *Journal of Personality and Social Psychology* 51, no. 6 (1986): 1173–1182.

27. D. P. MacKinnon, *Introduction to Statistical Mediation Analysis* (Routledge, 2012).

28. W. E. Chi, S. Huang, M. Jeon, E. S. Park, T. Melguizo, and A. Kezar, "A Practical Guide to Causal Mediation Analysis: Illustration With a Comprehensive College Transition Program and Nonprogram Peer and Faculty Interactions," *Frontiers in Education (Lausanne)* 7 (2022): 886722.

29. K. Imai, L. Keele, and T. Yamamoto, "Identification, Inference and Sensitivity Analysis for Causal Mediation Effects," *Statistical Science* 25, no. 1 (2010): 51–71.

30. D. Katz, J. Baptista, S. P. Azen, and M. C. Pike, "Obtaining Confidence Intervals for the Risk Ratio in Cohort Studies," *Biometrics* 34, no. 3 (1978): 469.

31. D. Tingley, T. Yamamoto, K. Hirose, L. Keele, and K. Imai mediation: R Package for Causal Mediation Analysis [Internet]. 2014. http://www.jstatsoft.org/.

32. K. Imai, L. Keele, D. Tingley, and T. Yamamoto "Identification, Inference and Sensitivity Analysis for Causal Mediation Effects," *Statistical Science* 25, no. 1 (2010).

33. S. Jones, C. Moulton, S. Swift, et al., "Association Between Delays to Patient Admission From the Emergency Department and All-Cause 30-day Mortality," *Emergency Medicine Journal* 39, no. 3 (2022): 168–173.

34. A. Guttmann, M. J. Schull, M. J. Vermeulen, and T. A. Stukel, "Association Between Waiting Times and Short Term Mortality and Hospital Admission After Departure From Emergency Department: Population Based Cohort Study From Ontario, Canada," *BMJ* 342, (2011): d2983.

35. P. K. Plunkett, D. G. Byrne, T. Breslin, K. Bennett, and B. Silke, "Increasing Wait Times Predict Increasing Mortality for Emergency Medical Admissions," *European Journal of Emergency Medicine* 18, no. 4 (2011): 192–196.

36. D. Byrne, J. G Browne, R. Conway, S. Cournane, D. O'Riordan, and B. Silke, "Mortality Outcomes and Emergency Department Wait Times – the Paradox in the Capacity Limited System," *Acute Medicine Journal* 17, no. 3 (2018): 130–136.

37. P. C. Gonçales, D. Pinto Júnior, P. de Oliveira Salgado, and T. C. Machado Chianca, "Relationship Between Risk Stratification, Mortality and Length of Stay in a Emergency Hospital," *Investigación y Educación en Enfermería* 33, no. 3 (2015): 424–431.

38. J. M. Zachariasse, N. Seiger, P. P. M. Rood, et al., "Validity of the Manchester Triage System in Emergency Care: A Prospective Observational Study," *PLoS One* 12, no. 2 (2017): e0170811.

39. H. L. Daebes, L. L. Tounsi, M. Nerlander, et al., "Association Between Triage Level and Outcomes at Médecins Sans Frontières Trauma Hospital in Kunduz, Afghanistan, 2015," *Emergency Medicine Journal* 39, no. 8 (2022): 628–633.

40. D. L. Markussen, H. S. Brevik, R. O. Bjørneklett, and M. Engan, "Validation of a Modified South African Triage Scale in a High-Resource Setting: A Retrospective Cohort Study," *Scandinavian Journal of Trauma, Resuscitation and Emergency Medicine* 31, no. 1 (2023): 13.

41. B. Son, J. Myung, Y. Shin, et al., "Improved Patient Mortality Predictions in Emergency Departments With Deep Learning Data-Synthesis and Ensemble Models," *Scientific Reports* 13, no. 1 (2023): 15031.

42. J. M. Zachariasse, V. van der Hagen, N. Seiger, K. Mackway-Jones, M. van Veen, and H. A. Moll, "Performance of Triage Systems in Emergency Care: A Systematic Review and Meta-Analysis," *BMJ Open* 9, no. 5 (2019): e026471.

43. J. S. Hinson, D. A. Martinez, S. Cabral, et al., "Triage Performance in Emergency Medicine: A Systematic Review," *Annals of Emergency Medicine* 74, no. 1 (2019): 140–152.

44. N. Farrohknia, M. Castrén, A. Ehrenberg, et al., "Emergency Department Triage Scales and Their Components: A Systematic Review of the Scientific Evidence," *Scandinavian Journal of Trauma, Resuscitation and Emergency Medicine* 19, no. 1 (2011): 42.

45. T. Levis-Elmelech, D. Schwartz, and Y. Bitan, "The Effect of Emergency Department Nurse Experience on Triage Decision Making," *Human Factors in Healthcare* 2 (2022): 100015.

46. E. Gómez-Angelats, Ò. Miró, E. Bragulat Baur, A. Antolín Santaliestra, and M. Sánchez Sánchez, "Triage Level Assignment and Nurse Characteristics and Experience," *Emergencias: Revista de la Sociedad Espanola de Medicina de Emergencias* 30, no. 3 (2018): 163–168.

47. H. Gorick, "Factors That Affect Nurses' Triage Decisions in the Emergency Department: A Literature Review," *Emergency Nurse* 30, no. 3 (2022): 14–19.

Supporting Information

Additional supporting information can be found online in the Supporting Information section.
SuppMat.