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The role of clinical and social criteria in intensive care unit admission decisions: Evidence from a medical decision-making tool

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Abstract

Background: In critical care settings, especially during surges such as the COVID-19 pandemic, physicians are often required to make rapid triage decisions under resource constraints. While clinical indicators should ideally guide these decisions, emerging research indicates that non-clinical factors—such as a patient's race or gender—may inadvertently affect judgment. **Aim:** This study aims to validate clinical profiles using a decision-making tool and examine the predictive role of clinical and social factors in intensive care unit (ICU) admission decisions under contingency conditions, such as during the COVID-19 pandemic. **Methods:** A total of 432 ICU admission decisions (trials) were collected from a simulated task in which nine ICU physicians evaluated 48 fictional patient profiles under conditions of limited bed availability. Each participant reviewed all profiles and selected half of the profiles for admission. Each profile included six clinical criteria (e.g., prognosis, comorbidities, and respiratory failure severity) and two non-clinical features (i.e., gender and race). The trial served as the unit of analysis. Multilevel logistic regressions assessed the predictive power of clinical and social variables on acceptance decisions, omission errors (rejecting qualified candidates), and false alarms (accepting less qualified candidates). **Results:** The findings demonstrate that participants relied primarily on clinical information: high-scoring profiles were admitted more often (67.4% and 52.5%) than lower-scoring ones (37.5% and 13.5%) ($p<0.001$). However, social factors also shaped decisions. Male candidates were more likely to be admitted than females ($b = -0.51$; $t = -4.35$; $p<0.001$; 95% confidence interval [CI] = [–0.75, –0.27]), and Black candidates were admitted more than White candidates ($b = -0.52$; $t = -3.34$; $p<0.001$; 95% CI = [–0.85––0.19]), even when less qualified, thereby suggesting possible overcorrection. **Conclusion:** Although clinical criteria primarily guided ICU admission decisions, social characteristics also subtly influenced outcomes. Together, these findings validate the novel decision-making paradigm as a valuable tool for assessing both clinical accuracy and the presence of social bias in triage contexts. They also provide empirical evidence that, under pressure and uncertainty, healthcare professionals may be susceptible to the influence of social cues. **Relevance for patient:** This study explores how critical care physicians decide who receives life-saving treatment in ICUs, especially during times of crisis when medical resources are limited. By simulating real-world triage situations, the research shows that even experienced clinicians may be influenced by non-clinical factors—such as a patient's race or gender—despite their intention to prioritize clinical indicators.

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These findings highlight the need for increased awareness and targeted training to reduce unconscious bias in clinical decision-making.

Keywords: Intensive care unit admission; COVID-19; Decision-making; Assessment tool; Social biases; Resource allocation

1. Introduction

The medical decision-making process in the context of intensive care unit (ICU) admission is inherently complex, particularly during times of crisis, such as the COVID-19 pandemic, when healthcare systems faced unprecedented pressure due to high patient volumes and limited resources.[1,2] The resulting imbalance between demand and ICU bed availability generated a scenario of resource scarcity, raising profound ethical and clinical challenges in prioritizing patients for life-saving care.[3]

In response, several international organizations issued guidelines aimed at promoting equity, transparency, and consistency in ICU admission protocols under resource-limited conditions.[4] However, despite these efforts, significant disparities in ICU capacity and emergency preparedness were evident across European healthcare systems. These structural differences contributed to uneven mortality outcomes and exposed vulnerabilities in healthcare infrastructures.[5] Moreover, early warning signs of the pandemic's spread were already visible in social media data before official responses were mobilized, highlighting discrepancies in institutional readiness and the timeliness of public health interventions.[6] Such variations not only shaped the trajectory of the pandemic across different regions but also exacerbated inequalities in ICU access and patient outcomes.

While clinical frameworks have been established to promote fairness in ICU admissions, particularly during crises such as the COVID-19 pandemic, evidence shows that medical decisions remain vulnerable to the influence of both patient-related and provider-related factors.[7] One underexplored yet critical contributor to inequities is the role of cognitive and social biases under contingency scenarios—an area well documented in social psychology.[8] When clinicians operate under intense pressure and cognitive load, they must process complex information rapidly, increasing their reliance on mental shortcuts or heuristics. While these strategies may improve efficiency, they can also unintentionally increase the likelihood of introducing social bias into clinical judgments.[9-11]

A growing body of interdisciplinary research suggests that resource scarcity may not only constrain logistical capacities in clinical environments but also influence the cognitive and social dynamics underlying decision-making. Under conditions of scarcity, individuals tend to exhibit increased sensitivity to social group distinctions, including heightened protection of perceived in-group members and increased vigilance or exclusion of out-group members.[12,13] Scarcity can therefore act as a psychosocial stressor that amplifies implicit social biases, particularly in time-sensitive and high-stakes contexts such as intensive care triage. During the COVID-19 pandemic, the acute shortage of ICU beds and the overwhelming demand for care reduced opportunities for deliberative, criterion-based reasoning—an essential safeguard in clinical decision-making. In such circumstances, non-clinical characteristics such as race, gender, or socioeconomic background may unconsciously influence clinical judgments.[14-16] Although clinicians are trained to prioritize clinical criteria, racial disparities in care have been documented across multiple domains. For instance, White patients are more likely to be referred for cardiac interventions than Black patients,[17] and disparities in pain management persist, with Black children receiving less analgesia than their White counterparts.[18] However, the literature also reports inconsistent findings, with some studies reporting no significant differences based on race, highlighting the complex and context-dependent nature of bias in clinical decision-making.[19]

More recently, attention has turned to racial disparities in access to and outcomes of intensive care, particularly among Black patients. Black racial groups experienced higher rates of ICU admission and poorer clinical outcomes compared to White patients.[20,21] For example, during the COVID-19 pandemic, Black patients were disproportionately represented in ICU admissions and experienced elevated in-hospital mortality. In addition, studies have shown that Black patients were less likely to receive invasive life-sustaining treatments, such as mechanical ventilation.[18] These inequities are not fully attributed to differences in socioeconomic status or comorbidities; as suggested by previous evidence, they are also likely to result from individual factors, such as implicit provider biases, and structural factors within the healthcare system.[22,23]

Previous studies have provided evidence of the complexity of ICU admission decisions[24,25]; however, many have relied on qualitative or retrospective approaches that, although rich in descriptive detail, offer limited capacity to isolate causal effects. For example, Gopalan and De Vasconcellos[25] employed a structured interview method—the "20 Questions" approach—to explore the decision-making rationale of ICU physicians. This design was effective in uncovering key themes in clinical reasoning but lacked experimental control and did not permit systematic manipulation of patient attributes, thereby limiting its ability to identify underlying biases.

In contrast, the present study introduces a controlled experimental paradigm using a medical decision-making tool (MDMT) specifically designed to examine how physicians integrate clinical and social information when making triage decisions under resource scarcity. Developed during the COVID-19 pandemic through an interdisciplinary collaboration between critical care specialists and social scientists, the MDMT presents participants with multiple standardized fictional patient profiles that systematically vary across six clinical criteria (e.g., comorbidities, prognosis) and two social attributes (gender and race).

This design offers two key methodological advantages. First, it allows for direct comparison of decision patterns across controlled conditions, thereby minimizing confounding factors and enhancing internal validity. Second, by simulating real-time decisions under high-pressure, resource-limited scenarios, the paradigm makes it possible to detect subtle, potentially unconscious social biases that might remain unacknowledged in self-reports or interviews.

The MDMT was specifically developed to assess two complementary outcomes: (i) decision-making accuracy, defined as the physician's ability to consistently prioritize the most clinically appropriate candidates; and (ii) social bias, operationalized as systematic variation in decision patterns based on non-clinical characteristics such as gender or race. By combining clinical precision with sensitivity to social determinants of care, this study provides a robust and scalable tool to the growing body of research on fairness and equity in critical care decision-making.

2. Methods

2.1. Study design and ethical approval

This study employed an experimental, within-subjects design to examine how clinical and social factors influence ICU admission decisions under conditions of medical resource scarcity. The study protocol was approved by a local Institutional Review Board (Approval No. 30/21), and all participants provided informed consent before participation, in accordance with the Declaration of Helsinki.

2.2. Participants

Nine ICU physicians (five males, four females) aged 30–62 years volunteered to participate and provided informed consent. All participants completed an online experiment consisting of a medical decision-making task followed by a demographic questionnaire. Although the number of participants was nine, each physician evaluated 48 fictional patient profiles, yielding a total of 432 decision trials. The unit of analysis for all statistical models was at the trial level.

2.3. Procedure

The decision-making task simulated a scenario in which ICU resources were limited, and physicians were required to triage 48 fictional patient profiles for ICU admission. The task was divided into two phases:

(i) Viewing phase: Participants passively viewed all 48 fictional patient profiles for one second each in a randomized order to gain an overview of the range of clinical profiles.
(ii) Selection phase: Participants reviewed each patient profile one at a time, again in random order, and were given the following instructions:

Imagine that 48 clinical cases are being reviewed for ICU admission. However, there are only 24 beds available. Your task is to admit the 24 clinical cases for which ICU admission is most appropriate and reject the 24 clinical cases for which admission is less appropriate. You will first view all clinical cases. When you are done reviewing the clinical cases, your task is to select half (24 clinical profiles) for ICU admission.

Admission decisions were made by clicking either the "Accept" or "Reject" button. There was no time limit for decision-making.

2.3.1. Materials and clinical profiles

Each clinical profile consisted of six pieces of information relevant to ICU triage: age (30–40 vs. 80–90); obesity (body mass index: 20–45); comorbidities (conditions included non-Hodgkin's lymphoma, acute leukemia, arterial hypertension, metastatic esophageal cancer, multiple myeloma, and diabetes); degree of respiratory failure (minimal to moderate or severe); clinical progression (stable or worsening); and prognosis (presence of organ failure, shock, serum lactate levels twice the normal range, or anuric acute kidney injury). Participants were instructed to consider all clinical information when making their decisions.

To operationalize clinical qualification in a standardized manner, each fictional patient profile was scored based on six clinical attributes: age, comorbidities, oxygen saturation, respiratory rate, organ failure status, and prognosis. Each attribute was evaluated by an expert panel of critical care physicians and assigned a value of 1 (less favorable) or 2 (more favorable), based on established triage guidelines and clinical judgment. The total clinical score for each profile was computed by summing the six attribute values, resulting in scores ranging from 6 (lowest qualification) to 12 (highest qualification).

To enhance internal consistency and eliminate potential outliers, profiles with extreme total scores (6, 11, or 12) were excluded from the final set. This decision avoided ceiling and floor effects while maintaining comparability between profiles. The remaining profiles—those with total scores of 7 to 10—were grouped into two levels of clinical qualification for analytical purposes: less qualified (scores of 7 or 8) and more qualified (scores of 9 or 10). This structured scoring system allowed for controlled variation across profiles, ensuring that physicians were exposed to clinically plausible yet systematically differentiated clinical profiles.

2.3.2. Social variables and experimental design

To introduce social information, each profile was paired with one of 16 blurred facial images. These images represented four demographic categories: Black male, White male, Black female, and White female (n = 4 per group). The images were randomly assigned across profiles, ensuring equal distribution by qualification level and gender. In addition, a "neutral" condition (no image) was included to assess the independent effect of gender and race. The final experimental design was a 2 (gender: Male vs. female) × 3 (race: Black vs. White vs. neutral) × 2 (qualification: More qualified vs. less qualified) within-subjects model. Given the within-subjects experimental design, the primary unit of analysis was the ICU admission decision (trial), not the physician. This approach allowed for a robust estimation of patterns across multiple decision points.

2.4. Statistical analysis

All statistical analyses were performed using JASP version 0.19.3 (Jasp Team, The Netherlands). Multilevel logistic regression models were estimated to account for the hierarchical structure of the data (trial-level decisions nested within physicians). The unit of analysis was the individual ICU admission decision (trial), yielding a total of 432 observations.

To assess task accuracy, we first fitted a multilevel logistic regression model with profile qualification (more qualified vs. less qualified) as the independent variable and admission decision (accept = 1, reject = 0) as the binary outcome. This model tested whether participants systematically preferred more clinically qualified profiles.

Next, we fitted a second set of multilevel logistic models that included clinical variables (e.g., age category, comorbidities, respiratory failure severity) and social variables (gender, race) as fixed effects. We also examined interaction effects between clinical and social predictors to assess whether social characteristics moderated the impact of clinical qualification.

Each model included a random intercept for the physician to accommodate within-participant correlations. Model outputs are presented as regression coefficients (b), standard errors (SE), Wald z-statistics, p-values, and 95% confidence intervals (CI).

3. Results

3.1. Validation of the clinical profiles

A total of 432 decisions were analyzed to assess whether profile qualification influenced ICU admission decisions. We first examined the differences in participants' selection of more qualified patient profiles and rejection of less qualified profiles. This analysis was crucial for assessing task accuracy—specifically, whether participants systematically used clinical profile qualification as a criterion in their decision-making process.

A multilevel logistic regression analysis was conducted, with clinical profiles (Profiles 7–10) as the independent variable and ICU admission decision (accept vs. reject) as the dependent variable. The model revealed a statistically significant effect of profile qualification on candidate acceptance, χ^2 (1, 3) = 16.114, with $p<0.001$, suggesting that participants used the qualification level of the profiles as a critical factor in their decisions.

As shown in Table 1, the probability of acceptance increased with clinical qualification: Profile 10 had a 67.4% acceptance rate, followed by Profile 9 (52.5%). In contrast, less qualified profiles—Profile 8 and Profile 7—had lower acceptance rates of 37.5% and 13.5%, respectively. These differences indicate that participants reliably used clinical profile information when selecting ICU candidates.

3.2. Clinical criteria as predictors of ICU admission

To assess the impact of clinical variables on ICU admission, a logistic regression model was applied, including six clinical parameters: age, obesity, comorbidities, degree of respiratory failure, clinical evolution, and prognosis. As displayed in Table 2, five out of six clinical parameters significantly predicted the likelihood of

Table 1. Descriptives of acceptance rate for each clinical profile

Profile	Acceptance rate (%)	SD	95% CI	
			LI	LS
7	13.5	0.065	0.049	0.319
8	37.5	0.092	0.217	0.565
9	52.5	0.081	0.368	0.676
10	67.4	0.071	0.522	0.796

Abbreviations: CI: Confidence interval; LI: Lower bound of confidence interval; LS: Upper bound of confidence interval; SD: Standard deviation.

Table 2. Clinical factors predicting the likelihood of accepting ICU candidates

Predictor	*b*	SE	*t*	*p*-value	95% CI of *b*	
					Lower	Upper
Intercept	0.104	0.371	0.280	0.779	−0.624	0.832
Age	−0.815**	0.188	−4.342	<0.001	−1.184	−0.446
Obesity	0.063	0.131	0.484	0.629	−0.195	0.321
Comorbidities	−0.659**	0.137	−4.817	<0.001	−0.929	−0.389
Respiratory failure	−0.798*	0.281	−2.838	0.005	−1.351	−0.245
Clinical evolution	−0.343*	0.139	−2.460	0.014	−0.616	−0.070
Prognosis	−0.589**	0.167	−3.531	<0.001	−0.917	−0.261

Note: *$p<0.05$ and **$p<0.01$.
Abbreviations: CI: Confidence interval; SE: Standard error.

candidate acceptance. The findings demonstrate that age, comorbidities, respiratory failure severity, clinical evolution, and prognosis were all statistically significant. In contrast, obesity had no significant predictive value.

Younger candidates (mean = 0.64; standard deviation [SD] = 0.07) were more likely to be accepted than older candidates (mean = 0.39; SD = 0.06); $b = -0.815$; SE = 0.188; $t = -4.342$; $p<0.001$; 95% CI = [−1.184, −0.446]). Candidates with less severe comorbidities (mean = 0.61; SD = 0.07) were more likely to be accepted than those with severe conditions (mean = 0.42; SD = 0.06; $b = -0.659$; SE = 0.137; $t = -4.817$; $p<0.001$; 95% CI = [−0.929, −0.389]. Similarly, profiles with severe respiratory failure were more likely to be accepted (mean = 0.65; SD = 0.07) than those with moderate respiratory failure (mean = 0.39; SD = 0.06; $b = -0.798$; SE = 0.281; $t = -2.838$; $p=0.005$; 95% CI = [−1.351, −0.245]).

Candidates with worsening clinical progression were more likely to be accepted (mean = 0.57; SD = 0.07) than those with stable progression (mean = 0.47; SD = 0.06; $b = -0.34$; SE = 0.14; $t = -2.46$; $p<0.01$; 95% CI = [−0.616, −0.070]). Finally, profiles with prognoses involving multiple organ failure were more likely to be accepted (mean = 0.61; SD = 0.07) compared to candidates without such complications (mean = 0.43; SD = 0.06; $b = -0.59$; SE = 0.17; $t = -3.53$; $p<0.001$; 95% CI = [−0.917, −0.261]). However, obesity was not associated with any significant difference in acceptance rates ($b = 0.063$; SE = 0.131; $t = 0.484$; $p=0.629$).

Figure 1 illustrates the effect of clinical criteria on ICU admission decisions, highlighting how these parameters shaped acceptance probability.

3.3. Social criteria as predictors of ICU admission decisions

A second analysis examined the influence of gender, race, and clinical profile qualification. As expected, more qualified candidates (mean = 0.63; SE = 0.09) were accepted more often than less qualified ones (mean = 0.27; SE = 0.07; $b = -0.76$; $t = -6.34$; $p<0.001$; 95% CI = [−0.99, −0.52]).

However, social factors also affected ICU admission decisions. Male candidates were significantly more likely to be accepted (mean = 0.57; SE = 0.09) compared to female candidates (mean = 0.32; SE = 0.08; $b = -0.51$; $t = -4.35$; $p<0.001$; 95% CI = [−0.75, −0.27]). Likewise, Black candidates were more likely to be accepted (mean = 0.51; SE = 0.10) than White candidates (mean = 0.32; SE = 0.09; $b = -0.52$; $t = -3.34$; $p<0.001$; 95% CI = [−0.85, −0.19]).

As displayed in Figure 2, a three-way interaction between profile qualification, gender, and race revealed a nuanced pattern. Female candidates reached acceptance rates above 50% when profiles were more qualified and presented with a neutral (no image) profile. In all other conditions, acceptance rates for female candidates fell below this threshold. In contrast, Black male candidates with less qualified profiles were accepted at rates similar to those with more qualified ones, suggesting potential overcorrection or compensatory bias. White male profiles with lower qualifications, and those with neutral images, had acceptance rates below 20%.

We then analyzed two types of decision errors:
(i) Omissions: Rejection of more qualified candidates
(ii) False alarms: Acceptance of less qualified candidates.

3.3.1. Omissions

More qualified female candidates were more likely to be rejected (mean = 0.24; SE = 0.04) compared to qualified male candidates (mean = 0.12; SE = 0.04; $b = 0.44$; $t = -2.80$; $p=0.01$; 95% CI = [0.13, 0.75]). Race had no significant effect when comparing Black versus White candidates ($b = 0.29$; $t = 1.475$; $p=0.14$; 95% CI = [−0.10, 0.68]), but candidates with no image (neutral profile) were

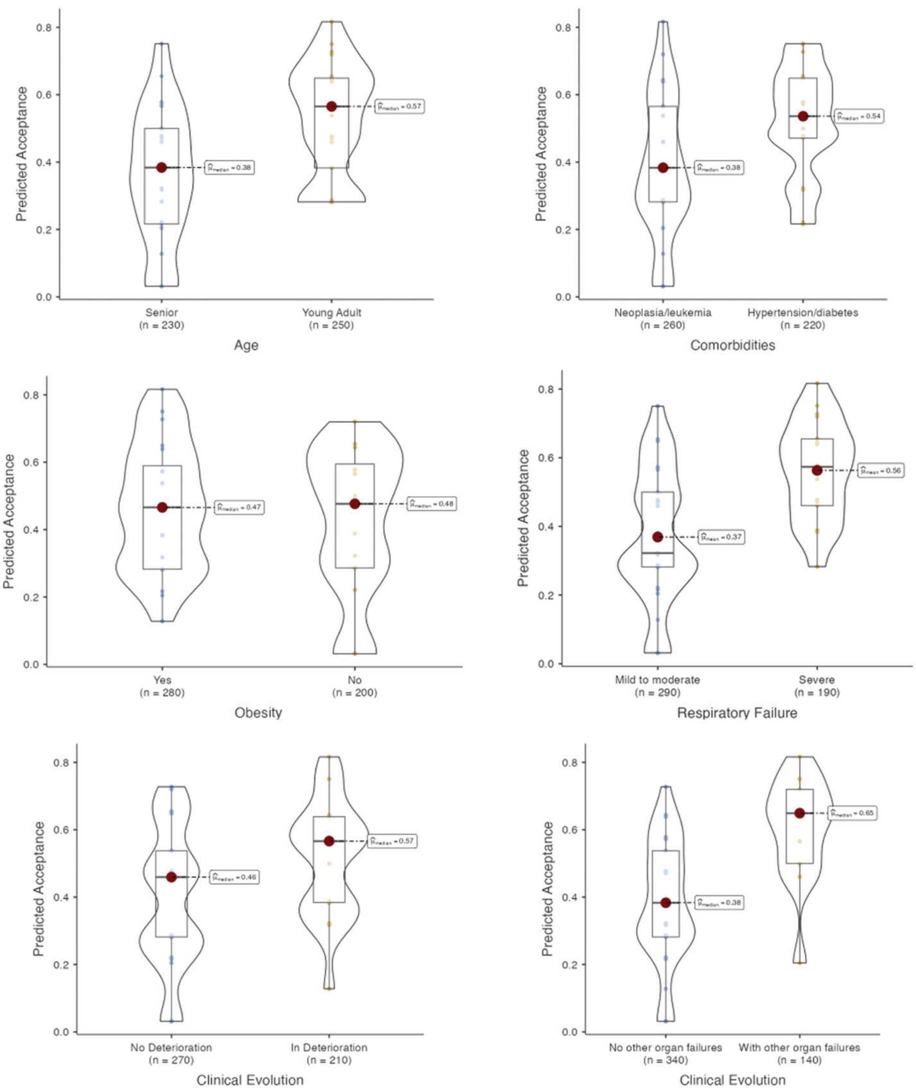

Figure 1. Effects of clinical criteria on intensive care unit admission decisions

less likely to be rejected ($b = -0.75$; $t = -2.66$; p=0.008; 95% CI [−1.30, −0.20].).

These findings are presented in Figure 3 and summarized in Table 3.

3.3.2. False alarms

No significant differences were observed in the acceptance rate of less qualified candidates based on gender ($b = -0.19$; $t = -0.79$; p=0.43; 95% CI = [−0.64, 0.26]) or race ($b = -0.19$; $t = -0.59$; p=0.56; 95% CI = [−0.84, 0.46]). However, as displayed in Figure 4 there was a near-significant interaction between gender and race ($b = 0.96$; $t = 1.79$; p=0.07; 95% CI [−0.09, 2.02]), suggesting a trend in which Black male candidates were more likely to be incorrectly accepted (mean = 0.28; SE = 0.06) than other groups (Table 4).

4. Discussion

The process of ICU admission decision-making is critical and complex, particularly in contexts of resource scarcity, such as during the COVID-19 pandemic. While guidelines are developed to ensure fairness, non-clinical factors—such as patient demographics—may unconsciously influence medical decisions. The present study examined the predictive role of clinical and social factors in ICU admission decisions using a validated MDMT, assessing both decision accuracy and potential biases.

The results provide strong evidence supporting the validity of the MDMT clinical profiles. Our findings indicate that participants consistently admitted more qualified profiles (Profiles 9 and 10), with acceptance rates above

Table 3. Predictors of omissions (rejection of qualified candidates)

Predictor	*b*	SE	*t*	*p*-value	95% CI for *b*	
					Lower	Upper
Intercept	−1.594	0.234	−6.812	<0.001	−2.053	−1.135
Gender	0.437*	0.156	2.798	0.005	0.131	0.743
Race (White vs. neutral)	−0.746*	0.280	−2.662	0.008	−1.296	−0.196
Race (White vs. Black)	0.293	0.198	1.475	0.140	−0.096	0.682
Gender-race (White vs. neutral)	0.345	0.255	1.352	0.176	−0.155	0.845
Gender-race (White vs. Black)	−0.012	0.194	−0.064	0.949	−0.392	0.368

Note: *$p<0.05$.
Abbreviations: CI: Confidence interval; SE: Standard error.

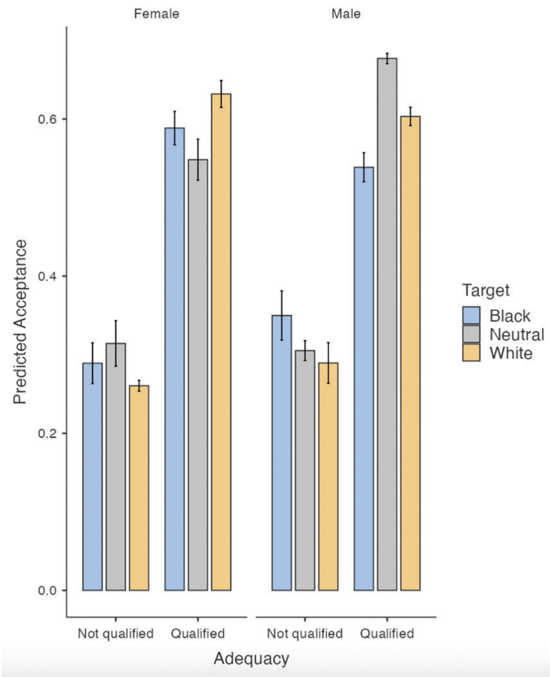

Figure 2. Effects of profile qualification, gender, and race on intensive care unit admission decisions

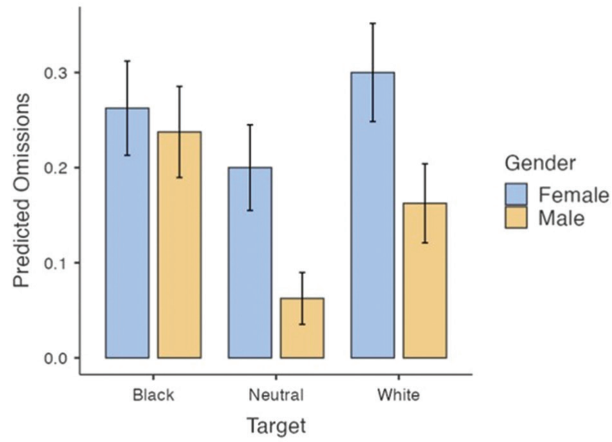

Figure 3. Effects of gender and race on omissions

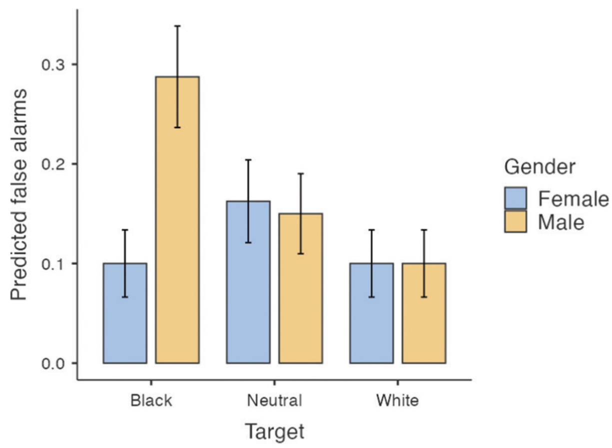

Figure 4. Effects of gender and race on false alarms

50%, while less qualified profiles (Profiles 7 and 8) were generally rejected, with acceptance rates below 50%. These findings demonstrate the tool's sensitivity in distinguishing clinical appropriateness, validating its use in simulating real-world ICU decision-making.

Beyond clinical criteria, the findings revealed subtle yet meaningful influences of social factors on decision-making outcomes. Male candidates were significantly more likely to be accepted (57%) compared to female candidates (32%), despite having similar clinical profiles. This gender disparity reflects patterns documented in prior research, where male patients often receive more aggressive interventions or are perceived as more clinically urgent.[26-28] These perceptions may be driven by implicit assumptions about gender and severity of illness, which can affect physician judgment even in controlled settings.

Racial-related differences were also observed. Black candidates had a higher acceptance rate (51%) than White candidates (32%), a finding that initially

Table 4. Predictors of false alarms (acceptance of less qualified candidates)

Predictor	*b*	SE	*t*	*p*	95% CI for *b*	
					Lower	Upper
Intercept	−2.412	0.438	−5.511	<0.001	−3.270	−1.554
Gender	−0.185	0.233	−0.795	0.427	−0.641	0.271
Race (White vs. neutral)	−0.282	0.411	−0.685	0.493	−1.088	0.524
Race (White vs. Black)	−0.194	0.332	−0.585	0.559	−0.844	0.456
Gender-race (White vs. neutral)	0.964	0.539	1.787	0.074	−0.092	2.020
Gender-race (White vs. Black)	−0.147	0.380	−0.387	0.699	−0.892	0.598

Abbreviations: CI: Confidence interval; SE: Standard error.

appears to contradict prior research documenting worse treatment outcomes and lower procedure rates for racial minorities.[29,30] However, further analysis suggests that this pattern may reflect compensatory behavior. Specifically, less qualified Black male candidates were admitted at rates similar to more qualified candidates, potentially indicating a motivation to avoid perceived racial bias. This interpretation aligns with aversive racism theory, which posits that individuals motivated to appear egalitarian may overcorrect their decisions in favor of historically marginalized groups in ambiguous contexts.[31]

These findings are consistent with the broader literature on healthcare disparities and highlight how contextual factors, such as medical contingency situations in high-stakes environments, can amplify the influence of cognitive heuristics in clinical judgment.[10,32] Importantly, such influences may not arise from deliberate and intentional bias but rather from scarcity-induced reliance on mental shortcuts—a common feature of decision-making under contingency circumstances.[8,12,33,34]

5. Limitations and future directions

While the findings provide important empirical evidence, some limitations should be acknowledged. Although the number of participating physicians was relatively small (n = 9), it is important to clarify that the unit of analysis in our study was the observed decision behavior in the randomized controlled trial, rather than the individual participant. Each of the nine ICU physicians made 48 independent ICU admission decisions, resulting in 432 unique trials. This trial-level dataset enables the identification of systematic patterns across diverse clinical scenarios and allows testing the effects of our experimental manipulations with adequate statistical power. This approach is consistent with established practices in cognitive neuroscience and decision science, where relatively small participant samples are often used, but a large number of within-subject observations provides sufficient power to detect meaningful effects.[35-37]

In the present study, concerns about generalizability refer more to the diversity of decision patterns observed than to the sample size per se. Using this methodological design, we were able to detect robust, statistically significant effects—including consistent patterns of clinical prioritization and evidence of social bias—at the behavioral level. While these effects were strong in our dataset, it is plausible that their magnitude may be even greater in larger and more heterogeneous physician samples, where factors such as training background, institutional culture, or other demographic characteristics could serve as important moderators.

Second, the MDMT employed an internal scoring system used to construct clinical profiles. Although the fixed scale (6–12) ensured consistency across conditions, it was not visible to participants and served only to categorize profiles based on expert-rated clinical attributes. Nonetheless, participants may have inferred implicit patterns across similar profiles, potentially relying on heuristics rather than naturalistic reasoning. To minimize this, profiles were randomized and diversified. Future studies could employ less structured or dynamic formats to further reduce perceived regularities and capture clinical reasoning more authentically.

Moreover, future studies may benefit from integrating training methodologies inspired by recent advances in medical artificial intelligence (AI).[38] While AI-based systems excel at extracting patterns from large-scale clinical data, they typically rely on retrospective observational inputs and lack experimental manipulation of social variables. Combining the predictive power of AI with controlled experimental paradigms like the MDMT could offer a more comprehensive understanding of how social information is cognitively processed and used in triage decisions, particularly under conditions of pressure and uncertainty.

Third, although the study identified patterns consistent with social bias, the underlying psychological mechanisms—such as implicit prejudice, stereotyping, or aversive bias—were not directly assessed. To better understand the cognitive and affective drivers of these decisions, future research could incorporate behavioral data with implicit measures (e.g., implicit association test), allowing researchers a more nuanced understanding of how social cues are cognitively processed and translated into clinical decisions during contingency scenarios characterized by uncertainty and pressure.

A further methodological consideration concerns the constrained scoring format used to represent clinical severity. While the structured nature of the MDMT mirrors the logic of real-world triage tools, it may also have encouraged pattern-seeking or compensatory strategies among participants, potentially introducing artificial consistency in responses. Exploring alternative formats—such as dynamic clinical scenarios or open-ended justifications—could provide richer data and mitigate the influence of response heuristics.

Finally, although this study focused on race and gender as social dimensions of interest, other socially relevant variables—such as socioeconomic status, immigration background, or disability—may also influence clinical decision-making. Future research should expand the scope of analysis to include these intersecting factors to capture the multidimensional nature of healthcare disparities more comprehensively.

6. Conclusion

Our findings support the use of the MDMT as an effective experimental paradigm to assess how both clinical and social information influence ICU admission decisions under conditions of resource scarcity. While the findings indicate that participants consistently prioritized more clinically appropriate candidates—indicating accurate clinical judgment—systematic patterns of gender and racial bias were also observed. These findings highlight the need to address intersectional biases in critical care environments, particularly during high-pressure decision-making.

The findings suggest that efforts to promote fairness in ICU triage should include the implementation of structured decision-making protocols, evidence-based support tools, and targeted training programs in implicit bias and aversive racism mitigation. As healthcare systems continue to face global crises requiring ethically complex resource allocation, ensuring equitable access to life-saving care must remain a central ethical and clinical priority.

From a policy and practice standpoint, these findings underscore the need for integrating bias-mitigating safeguards into ICU triage processes. These may include transparent eligibility criteria, anonymized review mechanisms, and AI-assisted decision-support systems designed with embedded fairness constraints. Investing in such systemic reforms is essential to strengthening public trust in healthcare systems.

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Conflict of interest

The authors declare they have no competing interests.

Author contributions

Conceptualization: All authors
Data curation: Filipa Madeira
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Methodology: All authors
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Writing–original draft: Filipa Madeira
Writing–review & editing: All authors

Ethics approval and consent to participate

The study protocol was approved by a local Institutional Review Board (Approval No. 30/21), and all participants provided informed consent before participation, in accordance with the Declaration of Helsinki.

Consent for publication

All participants were informed about the nature of the study and provided consent to participate; however, no individual data are published that would require additional consent for publication.

Availability of data

The dataset used and/or analyzed during the study is available from the corresponding author upon reasonable request. All data generated or analyzed during this study are included in this published article.

Further disclosure

Part of or the entire set of findings have been presented in the conference *International Congress of Psychology*, *Prague*, 2024 (August, 2024).

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