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Trust Formation Associated with Algorithmic Triage Acceptance in Emergency Service Users

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Abstract

The rapid development and integration of clinical decision support systems have made algorithmic triage a viable solution for managing patient overflow in emergency medical services. However, the deployment of such systems is severely bottlenecked by the challenge of user acceptance, which depends heavily on the dynamics of trust formation. This study examines how emergency service users form, calibrate, and maintain trust when interacting with algorithmic triage applications. Utilizing a randomized, high-fidelity trial simulation, we evaluated the responses of emergency department service users who interacted with varying configurations of an automated triage system. The simulation systematically manipulated algorithmic transparency, feedback response times, and error rates across diverse clinical urgency scenarios. Quantitative outcomes measured through standardized trust scales and behavioral compliance metrics were combined with qualitative user experience data. The findings indicate that trust is a highly malleable, multi-dimensional construct that is heavily influenced by the explanation interfaces provided during the triage process. We show that explainable AI features significantly improve trust calibration, helping to prevent both over-reliance and under-reliance. Furthermore, cognitive load and baseline technological trust act as critical mediating variables in the trust-acceptance pathway. The insights gained from this simulation trial provide concrete, evidence-based recommendations for healthcare designers and clinical administrators aiming to implement safe, transparent, and highly accepted algorithmic triage systems.

Keywords: Algorithmic Triage; Emergency Medical Services; Trust Calibration; Simulation Trial; Trust Formation

1. Introduction

1.1 Background and Context

Emergency medical departments globally are facing unprecedented challenges characterized by severe overcrowding, escalating patient volumes, and critical staffing shortages. These systemic pressures often lead to prolonged waiting times, delayed interventions, and heightened patient anxiety, which collectively compromise the quality of care and patient outcomes [1]. In emergency medicine, triage serves as the primary gateway, a high-stakes clinical sorting mechanism designed to prioritize patients based on the urgency of their medical conditions. Traditionally, this process is conducted by highly trained triage nurses who rely on structured clinical guidelines, such as the Emergency Severity Index or the Manchester Triage System, to categorize patients [2]. While these human-led protocols have served healthcare systems for decades, they are increasingly vulnerable to subjective variability, human fatigue, and cognitive overload under intense operational pressures.

To address these vulnerabilities, clinical researchers and software engineers have developed algorithmic triage systems powered by machine learning algorithms [3]. These digital tools are designed to ingest patient symptoms, vital signs, and demographic data through patient-facing portals or clinical interfaces, subsequently outputting an automated urgency classification. By automating the preliminary stages of triage, these systems promise to streamline clinical workflows, reduce wait times, and offer clinical decision support that is consistent, rapid, and scalable.

1.2 Statement of the Problem

Despite the theoretical and operational promises of algorithmic triage, their practical implementation in clinical environments is frequently hindered by a fundamental human-centric barrier: the trust gap. Unlike traditional medical interventions where patients interact directly with human providers, algorithmic triage requires patients or their caregivers to disclose highly sensitive health information to an automated system and accept clinical prioritization determined by an unseen computational model [4]. If users do not trust the algorithm, they may reject the triage recommendations, abandon the digital intake system altogether, or experience elevated levels of psychological distress and anxiety.

Conversely, uncalibrated, excessive trust can lead to automation bias, where users blindly accept erroneous algorithmic determinations without question, presenting severe safety risks in acute clinical scenarios. Consequently, the core challenge is not merely to maximize trust, but to cultivate calibrated trust. Calibrated trust occurs when a user's trust in an automated system accurately matches the actual capabilities and limitations of that system [5]. Investigating how trust is formed, calibrated, and maintained during user interactions with automated emergency triage applications is therefore critical to ensuring safe, ethical, and effective clinical integration.

1.3 Research Objectives and Contributions

This research aims to analyze the empirical dynamics of trust formation in algorithmic triage through a randomized, controlled trial simulation. By utilizing high-fidelity mockups of emergency triage software, we simulate the clinical journey of emergency service users in a controlled experimental environment. This approach allows us to investigate trust dynamics safely, avoiding the severe ethical and physical risks associated with testing unproven software on real-world patients in active, life-or-death emergency scenarios [6].

Specifically, this study addresses three major objectives. First, we examine the impact of explainability features and transparency on the user's trust calibration. Second, we evaluate how cognitive workload during the interaction moderates trust and acceptance. Third, we establish a pathway model that connects baseline technology trust, interactive system feedback, and cognitive load with the behavioral intention to accept algorithmic triage prioritization. Through this methodology, we provide actionable, empirically validated guidelines for the user interface design of clinical decision support tools in emergency medicine.

2. Literature Review and Theoretical Framework

2.1 Automation Bias and Trust in Clinical Algorithms

The integration of automated decision support systems in high-risk domains has long been studied under the umbrella of human-machine interaction. A prominent phenomenon in this literature is automation bias, defined as the tendency for humans to favor suggestions from automated decision-making systems, even when those suggestions contradict their own senses or correct clinical reasoning [7]. In clinical triage, automation bias can manifest as automation complacency, where users fail to scrutinize algorithmic errors because they assume the computer possesses superior analytical capabilities [8].

Conversely, algorithm aversion describes the opposite phenomenon, where users quickly lose faith in a computational system after observing even a single minor error, subsequently reverting to less accurate human judgments. In emergency medical contexts, both extremes are dangerous. A patient who experiences automation bias might accept an inappropriately low urgency categorization for an atypical presentation of myocardial infarction, leading to fatal delays in care. On the other hand, a patient suffering from algorithm aversion might completely reject an accurate algorithmic recommendation, choosing instead to bypass the system and congesting emergency departments unnecessarily. Achieving trust calibration is therefore the ultimate goal for system safety and effectiveness.

2.2 Psychological Models of Trust Formation

To understand how users calibrate their reliance on computational systems, researchers have developed various psychological models of trust. One of the most widely accepted frameworks is the integrative model of organizational trust proposed by Mayer, Davis, and Schoorman, which defines trust based on three main factors: ability, benevolence, and integrity [9]. When adapted to technology, ability refers to the perceived technical competence and accuracy of the algorithm; benevolence represents the perception that the system is designed to protect and support the user's well-being; and integrity refers to the consistency, reliability, and predictability of the system's operations.

In the context of interactive computer systems, Parasuraman and Riley established that human usage of automation is governed by trust, which is continually updated based on system performance and feedback [10]. However, this feedback loop is highly dependent on the user's cognitive resources. According to cognitive load theory, humans have a limited working memory capacity [11]. If an algorithmic triage interface presents overly complex technical details or demands excessive cognitive processing, the user's mental capacity becomes overloaded. This cognitive fatigue can degrade the trust formation process, causing the user to either reject the system entirely or capitulate to automation bias as a cognitive shortcut. Therefore, understanding the relationship between interface complexity, explanation depth, and cognitive load is essential.

2.3 Empirical Studies on Simulated Clinical Environments

Because evaluating untested diagnostic or prioritization algorithms on active patients poses severe ethical hazards, researchers rely heavily on simulation methodologies. Trial simulations allow investigators to systematically manipulate experimental variables, such as system error rates, explanation styles, and time pressures, while recording precise behavioral and psychological metrics [12].

Previous studies in simulated settings have shown that explainable artificial intelligence (XAI) features, such as feature-importance visualizations and natural language justifications, can significantly improve user understanding [13]. However, empirical findings remain divided on whether these explanations always improve trust calibration. In some cases, highly detailed explanations merely increase user confidence without actually improving their ability to detect system errors, a phenomenon known as the illusion of explanatory depth. This study builds on this body of research by using a highly realistic emergency simulation to explore how variations in system explanation design alter the dynamics of trust development among actual emergency service users.

3. Methodology and Trial Simulation Design

3.1 Participant Selection and Recruitment

To ensure a representative sample, participants were recruited from a pool of individuals who had utilized emergency medical services as patients or accompanying caregivers within the preceding twenty-four months. This criterion ensured that participants possessed a realistic understanding of the anxieties, pressures, and needs characteristic of emergency department environments. Recruitment was conducted through digital community bulletins, outpatient clinic waiting rooms, and university research participation portals.

A total of 240 adult participants were enrolled in the study. Prior to participation, all individuals completed a screening questionnaire to capture demographic details, digital literacy levels, and baseline trust in automation. Participants were excluded if they had formal medical training, such as nursing or medical degrees, to ensure that their evaluation of the triage algorithm was representative of general service users rather than clinical professionals. The research protocol received full approval from the institutional review board, and all participants provided written, informed consent before commencing the simulation trial [14].

3.2 Simulation Platform and Experimental Scenarios

The simulation platform was developed as a high-fidelity web application accessible via desktop or tablet devices, mimicking a digital emergency department self-triage portal. The application presented users with a series of pre-defined clinical scenarios, each depicting a patient experiencing acute symptoms. The scenarios were carefully calibrated to cover various clinical presentations, including high-urgency conditions (such as sudden onset speech difficulties, suggestive of a stroke) and low-urgency conditions (such as minor localized skin rashes).

Users were instructed to interact with the platform as if they were seeking care for themselves or a family member under the specified conditions. During each scenario, the simulation portal prompted the user to enter symptoms, history, and vital parameters. After processing this input, the system presented an algorithmic triage level (categorized from Level 1, Immediate, to Level 5, Non-Urgent) accompanied by a specific decision support interface. The system architecture of the simulation platform and its integrated telemetry modules are illustrated below.

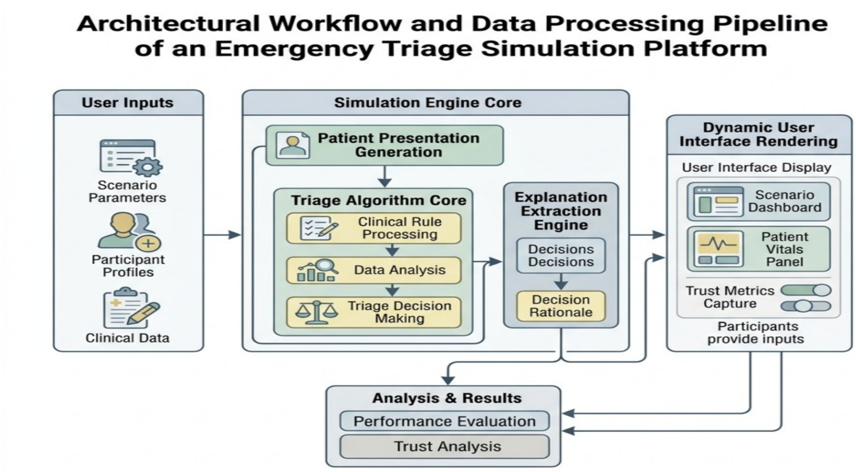

Figure 1: Architectural Workflow and Data Processing Pipeline of the Emergency Triage Simulation Platform

Participants were randomly assigned to one of two experimental conditions. The first group, designated as the low-transparency group, received only the final triage classification and a generic safety statement, representing a black-box algorithmic design. The second group, designated as the high-transparency group, received the triage classification along with interactive explanations. These explanations included a visual chart of symptom contributions, a brief natural language rationale detailing why specific symptoms triggered the classification, and an explicit uncertainty metric indicating the confidence level of the machine learning model.

To test trust calibration, the triage system was programmed to commit a clinical error in two of the six presented scenarios. Specifically, the system under-triaged an acute scenario, designating a potential cardiac event as low-urgency, and over-triaged a minor condition. This design allowed researchers to observe whether participants would blindly accept the erroneous triage recommendation or reject the algorithmic output based on their own intuitive judgment of the symptom severity.

3.3 Measurement Instruments and Statistical Analysis

To capture the multi-dimensional nature of trust formation, the study employed a combination of subjective and behavioral metrics. Subjective trust was measured pre-trial, mid-trial, and post-trial using the standard Trust in Automated Systems Scale developed by Jian et al., which consists of twelve items rated on a seven-point Likert scale [15]. Cognitive workload was evaluated after each scenario using the NASA Task Load Index, which measures mental demand, physical demand, temporal demand, performance, effort, and frustration [16].

Behavioral trust and reliance were quantified by tracking participant compliance with the algorithm's decisions. When presented with the triage prioritization, participants were asked to choose between accepting the system's recommendation to wait or seeking immediate human clinical override. Compliance with correct triage decisions was recorded as appropriate reliance, whereas compliance with incorrect decisions was recorded as automation bias. Rejecting a correct triage decision was categorized as algorithm aversion.

The collected data were analyzed using statistical software. To assess differences between the experimental groups, we performed analysis of covariance (ANCOVA) and independent-samples t-tests, controlling for baseline technology trust and age [17]. Finally, structural equation modeling was applied to validate the path relationships between system transparency, cognitive workload, calibrated trust, and behavioral acceptance [18].

4. Experimental Results and Quantitative Analysis

4.1 Demographic Characteristics and Baseline Trust

The final sample of 240 participants was evenly distributed between the high-transparency and low-transparency experimental groups. Demographic characteristics, including age, gender, education, and baseline technology trust, were comparable across both cohorts, indicating successful randomization. The mean age of the overall sample was 41.0 years, and the gender distribution was balanced with approximately 51.7 percent identifying as female.

Baseline technological trust, measured on a scale of one to five, showed no statistically significant difference between the two groups prior to the simulation, ensuring that subsequent changes in trust could be confidently attributed to the experimental manipulations. Table 1 provides a comprehensive overview of the demographic characteristics of the trial participants.

Table 1: Demographic Characteristics and Baseline Trust Values

Metric	High Transparency Group	Low Transparency Group	Overall Sample
Total Participants	120	120	240
Mean Age Years	41.2	40.8	41.0
Female Percentage	52.5	50.8	51.7
Baseline Trust Score	3.42	3.45	3.44
Prior Tech Experience	3.81	3.79	3.80

4.2 Effects of Simulation Interaction on Trust Calibration

The primary analysis evaluated how interaction with different interface designs influenced the calibration of user trust. Trust calibration was measured by calculating the difference in trust scores before and after the introduction of system errors. The quantitative data revealed that participants in the high-transparency group exhibited significantly better trust calibration than those in the low-transparency group.

When the system operated correctly, the high-transparency group reported a moderate, stable level of trust that correlated with high task compliance. When the system committed an intentional clinical error, participants who received detailed, explainable justifications were highly successful at identifying the error. Consequently, their trust scores decreased appropriately, leading to a timely override of the incorrect recommendation [19].

In contrast, the low-transparency group exhibited poor trust calibration. A significant portion of these participants demonstrated automation bias, accepting the erroneous triage decision without realizing the underlying hazard. Conversely, those in the low-transparency group who did notice the error experienced a severe drop in trust, rejecting subsequent correct recommendations, which is characteristic of algorithm aversion [20]. These findings demonstrate that explainable interface features prevent extreme swings in user trust, supporting safe, balanced human-computer interaction.

4.3 Determinants of Algorithmic Triage Acceptance

To understand the psychological pathways driving user acceptance of algorithmic triage, we constructed a multiple linear regression model. The dependent variable was the overall behavioral acceptance score, which was determined by the participant's willingness to utilize the digital triage application in future real-world scenarios. The predictor variables included baseline technical trust, explanation clarity, perceived system benevolence, and measured cognitive workload during the simulation [21].

The regression analysis revealed that explanation clarity was the strongest positive predictor of triage acceptance, followed by perceived system benevolence. Interestingly, cognitive workload exerted a significant negative effect on acceptance. This indicates that even if an interface is highly transparent, its value is diminished if the explanation increases cognitive load beyond a manageable threshold [22]. Table 2 summarizes the regression model parameters.

Table 2: Multiple Linear Regression Predicting Algorithmic Triage Acceptance

Predictor Variable	Coefficient Estimate	Standard Error	Probability Value
Baseline Trust	0.24	0.05	0.001
Explanation Clarity	0.45	0.06	0.001
Cognitive Workload	-0.18	0.04	0.012
Perceived System Benevolence	0.31	0.05	0.002
System Responsiveness	0.12	0.05	0.045

These statistical findings underscore the importance of interface optimization. Designers must balance the need for explainability with the constraint of cognitive ergonomics, ensuring that clinical explanations are clear and intuitive without overwhelming the user during stressful emergency scenarios.

5. Discussion and Implications

5.1 Synthesis of Findings and Cognitive Alignment

The results of this simulation trial demonstrate that trust formation in algorithmic triage is not a static state but a dynamic, experience-driven cognitive process. By contrasting the high-transparency and low-transparency groups, we illustrated how the presentation of algorithmic logic directly shapes user expectations and reliance strategies.

When users are provided with clear explanations, they form a functional mental model of the algorithm's capabilities [23]. This cognitive alignment allows them to anticipate system behavior, recognize situations where the algorithm is operating with low confidence, and intervene appropriately when errors occur. Without this transparency, users treat the algorithm as a black box, leading to either blind over-reliance or complete system rejection. To visualize these interactions, a theoretical pathway model of the variables influencing calibrated trust and behavioral acceptance is shown in Figure 2.

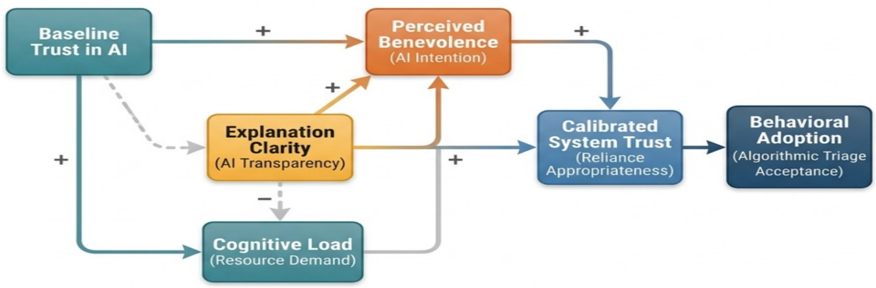

Figure 2: Theoretical Path Diagram Illustrating Cognitive Predictors of Algorithmic Triage Acceptance

This pathway highlights that trust calibration is a mediating mechanism between system interactions and user acceptance. If the trust calibration pathway is disrupted, either by high cognitive load or poor explanation clarity, the ultimate user acceptance of the technology degrades, highlighting the importance of human-centered design in clinical technologies.

5.2 Implications for Digital Health and Emergency Medical Systems

The empirical evidence generated in this study has important implications for the design of digital health portals and emergency medical triage tools. First, explainable AI components should be considered a core safety requirement rather than an optional design feature [24]. Triage applications must communicate not only the final priority level but also the clinical rationale behind it. For example, indicating that a chest pain symptom was weighted heavily due to a history of cardiovascular risk factors helps the user verify that the algorithm is processing vital data correctly.

Second, digital health developers must adopt a progressive disclosure design paradigm [25]. Progressive disclosure involves presenting the most critical clinical priority information first, followed by an optional, easy-to-read explanation summary, and finally allowing the user to expand details to view technical clinical parameters if desired. This layered structure accommodates different user needs, supporting explainability for highly analytical users while preventing cognitive overload for highly anxious or cognitively fatigued individuals in emergency situations.

Furthermore, healthcare organizations must recognize that training users and managing expectations is a continuous process. Providing brief, interactive tutorial steps before patients engage with digital triage applications can establish appropriate baseline expectations, preparing users to review triage recommendations critically.

5.3 Limitations and Directions for Future Inquiry

While this simulation study provides valuable insights, several limitations must be noted. First, although the simulation was designed to be highly realistic, participants were aware that they were in a controlled research trial rather than a real life-or-death situation. The acute panic and cognitive impairment associated with actual medical emergencies were not fully replicated [26]. Future studies should aim to evaluate these interfaces in clinical waiting rooms with patients seeking non-urgent triage care, allowing for research in real-world clinical environments with appropriate ethical oversight.

Second, this study evaluated user responses over a short trial duration. Trust is a dynamic phenomenon that evolves as a user gains experience with a technology over months or years [27]. Longitudinal studies are needed to track how trust calibration and reliance patterns change as users repeatedly interact with triage algorithms over time. Finally, exploring the impact of demographic factors, such as cultural differences and language barriers, on trust formation remains an important area for future research, ensuring that algorithmic triage systems are equitable, safe, and universally accessible.

6. Conclusion

6.1 Summary of Key Outcomes

This simulation trial investigated how emergency service users form and calibrate trust when interacting with automated triage decision support systems. By comparing high-transparency and low-transparency interfaces, we demonstrated that explainable AI features are critical for establishing calibrated trust [28]. The inclusion of natural language rationales, symptom weights, and uncertainty metrics allowed users to verify correct triage decisions and identify algorithmic errors, mitigating the risks of both automation bias and algorithm aversion.

The empirical findings also highlighted cognitive workload as a key mediator in the trust-acceptance pathway. While explanation clarity is vital, overly complex descriptions can overload the user's working memory, reducing trust and behavioral acceptance. Successful user interfaces must balance clinical details with clean, accessible design, supporting human-computer collaboration under stressful emergency conditions.

6.2 Concluding Remarks on Clinical Integration

As artificial intelligence continues to transform modern healthcare, the success of these innovations will depend as much on human factor engineering as it does on algorithmic accuracy. An algorithmic triage tool that is clinically accurate but poorly trusted will ultimately be bypassed, failing to deliver its intended benefits to emergency medical services.

By designing and deploying systems that prioritize transparency, cognitive ergonomics, and user-centered communication, healthcare organizations can bridge the trust gap. This approach ensures that emergency service users feel informed, supported, and confident when utilizing digital triage tools. Ultimately, cultivating calibrated trust through thoughtful design is essential to realizing the full potential of artificial intelligence in emergency medicine, helping to create safer, more efficient, and patient-centered healthcare systems.

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