Journal of Cyber-Physical Security and Robotics
Volume 02, Issue 2, 13-19, 2026

Research Article

Explainable Artificial Intelligence for Enhancing Trust in Autonomous Systems

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Received: 20th May, 2026 Accepted: 03th June, 2026

Abstract

Autonomous systems—ranging from self-driving vehicles to robotic surgical assistants and automated financial decision engines—are increasingly entrusted with consequential, safety-critical decisions. Yet their reliance on opaque, high-dimensional machine learning models has produced a persistent "trust gap" between system capability and human willingness to rely on these systems. This study investigates whether Explainable Artificial Intelligence (XAI) techniques can measurably enhance user trust, calibrate reliance, and improve decision quality in interactions with autonomous systems. Using a mixed-methods experimental design, 312 participants interacted with a simulated autonomous driving and decision-support platform under six explanation conditions (a black-box baseline and five XAI methods: SHAP, LIME, Grad-CAM, counterfactual explanations, and integrated gradients). Quantitative trust was measured via a validated 7-point Likert instrument, behavioral reliance was logged, and qualitative interviews probed the mechanisms underlying trust formation. Results indicated that all XAI conditions produced significantly higher trust than the black-box baseline (mean increase of 2.3 to 2.9 points, $p < .001$), with counterfactual explanations yielding the highest trust ($M = 6.02$, $SD = 0.31$). Trust scaled monotonically with explanation fidelity, and appropriate (calibrated) reliance—rather than raw trust—was the strongest predictor of decision accuracy. Qualitative analysis revealed that perceived transparency, actionability, and consistency drove trust formation. We conclude that XAI is a necessary but not sufficient condition for trustworthy autonomy: explanation quality, not mere presence, determines whether trust is appropriately calibrated. Implications for human-centered design, regulation, and future research are discussed.

Keywords: Explainable artificial intelligence, autonomous systems, human-AI trust, reliance calibration, interpretability

Introduction

Background and Context

The proliferation of autonomous systems represents one of the most significant technological transformations of the early twenty-first century. Autonomous vehicles navigate complex urban environments, clinical decision-support systems recommend diagnoses and treatments, and algorithmic agents execute high-frequency trades and allocate credit. The predictive power underpinning these systems derives largely from deep neural networks and ensemble methods whose internal representations are distributed across millions of parameters. While such models frequently surpass human performance on narrow tasks, their decision processes are effectively opaque to the humans who must supervise, collaborate with, or be governed by them (Adadi & Berrada, 2018; Doshi-Velez & Kim, 2017).

This opacity creates a fundamental tension. Trust—defined here as the willingness of a party to be vulnerable to the actions of another based on positive expectations (Mayer, Davis, & Schoorman, 1995)—is the psychological glue of effective human-automation collaboration. When trust is absent, capable systems are underutilized or rejected; when trust is excessive and uncalibrated, users over-rely on systems and fail to intervene when they should (Lee & See, 2004). Explainable Artificial Intelligence (XAI) has emerged as the dominant proposed remedy, promising to render model behavior intelligible and thereby support appropriate, calibrated trust (Gunning et al., 2019; Arrieta et al., 2020).

Despite a rapidly expanding XAI literature, empirical

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evidence that explanations actually enhance trust—rather than merely satisfying intuitions or regulatory checkboxes—remains fragmented and at times contradictory. Some studies report substantial trust gains from explanation, while others find that poor or misleading explanations can inflate unwarranted confidence (Bansal et al., 2021; Poursabzi-Sangdeh et al., 2021). The present study addresses this gap with a controlled, multi-method investigation of how distinct XAI techniques affect trust and reliance in autonomous systems.

Hypotheses

Grounded in the trust-in-automation framework and prior interpretability research, we test four hypotheses

- H1: Exposure to any XAI explanation will produce significantly higher user trust than a black-box baseline that provides no explanation.
- H2: Trust will increase monotonically with explanation fidelity, the degree to which an explanation faithfully reflects the underlying model's reasoning.
- H3: Explanation method will moderate trust, such that contrastive and example-based methods (counterfactual explanations) yield higher trust than purely attributional methods.
- H4: Calibrated reliance, rather than raw trust magnitude, will be the strongest predictor of decision accuracy in human-AI teams.

Significance of the Study

This research contributes on three fronts. Theoretically, it integrates the computational XAI literature with the psychological trust-in-automation literature, clarifying the causal pathway from explanation properties to trust outcomes. Methodologically, it employs a mixed-methods design that pairs controlled behavioral experimentation with qualitative inquiry, addressing the over-reliance on self-report alone that characterizes much prior work. Practically, the findings inform the design of trustworthy autonomous systems and provide empirical grounding for emerging regulatory frameworks—such as the EU AI Act—that mandate explainability for high-risk applications.

Literature Review

The literature relevant to this study spans three intersecting domains: the technical foundations of XAI, the psychology of human-automation trust, and empirical evaluations linking the two.

Technical Foundations of XAI

XAI methods are commonly taxonomized along two axes: intrinsic versus post-hoc interpretability, and model-specific versus model-agnostic scope (Arrieta et al., 2020; Molnar, 2020). Intrinsically interpretable models—linear models, decision trees, and rule lists—offer transparency by construction but often sacrifice predictive performance on complex perceptual tasks. Post-hoc methods instead explain already-trained black-box models. Among model-agnostic post-hoc techniques, LIME approximates local decision boundaries with sparse linear surrogates (Ribeiro, Singh, & Guestrin, 2016), while SHAP unifies feature-attribution methods under a game-theoretic Shapley-value foundation, providing local accuracy and consistency guarantees (Lundberg & Lee, 2017). For convolutional networks, gradient-based saliency methods such as Grad-CAM produce visual heatmaps highlighting influential image regions (Selvaraju et al., 2017), and integrated gradients attribute predictions to input features via a path-integral formulation (Sundararajan, Taly, & Yan, 2017). Counterfactual explanations, by contrast, identify minimal input changes that would alter the model's output, offering actionable, contrastive accounts that align with human explanatory expectations (Wachter, Mittelstadt, & Russell, 2017; Miller, 2019).

The Psychology of Human-Automation Trust

Trust in automation is widely modeled as a dynamic attitude shaped by the perceived performance, process, and purpose of a system (Lee & See, 2004). Critically, the goal of trustworthy design is not to maximize trust but to calibrate it so that reliance matches actual system reliability. Miscalibration manifests as disuse (under-trust) or misuse (over-trust), both of which degrade joint human-AI performance (Parasuraman & Riley, 1997). Mayer et al.'s (1995) integrative model identifies ability, benevolence, and integrity as antecedents of trust; in the automation context, transparency about system reasoning is hypothesized to signal integrity and ability, thereby supporting calibrated trust.

Empirical Evaluations Linking XAI and Trust

Empirical findings are mixed. Several controlled studies report that explanations increase trust and acceptance (Gunning et al., 2019), and that transparency improves perceived fairness. However, a prominent counter-current demonstrates that explanations can induce automation bias: users presented with plausible-looking but unfaithful explanations over-trust incorrect recommendations (Bansal et al., 2021; Poursabzi-Sangdeh et al., 2021). Miller (2019) argues that effective explanations must be contrastive, selective, and social—properties that attribution-based heatmaps frequently lack. This tension motivates our focus on explanation fidelity and method type as moderators, and our behavioral measurement of reliance rather than trust attitudes alone. Table 1 summarizes representative prior studies.

Table 1: Representative Prior Studies on XAI and Human Trust

Study	*XAI Method*	*Domain*	*Key Finding*
Ribeiro et al. (2016)	LIME	Text/Image	Local surrogates improved user inspection of model trust
Lundberg & Lee (2017)	SHAP	Tabular	Consistent attributions; improved interpretability
Selvaraju et al. (2017)	Grad-CAM	Vision	Visual saliency increased perceived transparency
Bansal et al. (2021)	Mixed	Decision support	Explanations can increase over-reliance on errors
Poursabzi-Sangdeh (2021)	Linear	Forecasting	More transparency ≠ better error detection
Wachter et al. (2017)	Counterfactual	Legal/Credit	Actionable, GDPR-aligned explanations

Methodology

3.1 Research Design

We employed a convergent parallel mixed-methods design combining a between-subjects controlled experiment (quantitative strand) with semi-structured interviews (qualitative strand). The quantitative strand used a 6 (explanation condition) × 2 (autonomy level: fully autonomous vs. human-in-the-loop) factorial design. The qualitative strand explored the subjective mechanisms underlying trust formation. Integration occurred at the interpretation stage, where qualitative themes were used to explain quantitative patterns.

Participants and Datasets

A total of 312 participants (M_age = 34.6, SD = 9.8; 51% female, 48% male, 1% non-binary) were recruited via a stratified online panel to approximate general-population demographics. Participants were randomly assigned across the twelve experimental cells (n ≈ 26 per cell). The autonomous system stimulus combined two datasets: (a) a publicly available urban-driving perception dataset comprising 15,000 annotated dashcam frames, and (b) a synthetic financial decision-support dataset of 40,000 loan-approval records. A gradient-boosted ensemble and a convolutional neural network served as the underlying autonomous models, achieving 92.4% and 89.7% held-out accuracy respectively.

Data Collection Methods

Each participant completed 24 decision trials in which the autonomous system issued a recommendation (e.g., brake/continue; approve/deny). Depending on condition, the recommendation was accompanied by no explanation (baseline) or one of five XAI explanations. After each trial, participants rated trust on a validated 7-point scale adapted from Jian, Bisantz, and Drury (2000) and chose whether to accept or override the recommendation (behavioral reliance). System logs captured response latency and override decisions. Following the task, 36 participants (six per condition) completed 25-minute semi-structured interviews.

Data Analysis Procedures

Quantitative data were analyzed using mixed-effects ANOVA with explanation condition and autonomy level as fixed factors and participant as a random effect. Planned contrasts compared each XAI condition against the baseline. Explanation fidelity was operationalized as proxy-to-model output agreement and entered as a continuous predictor in a linear mixed model. Calibrated reliance was computed as the agreement between participants' override decisions and ground-truth model correctness, and regressed on decision accuracy. Qualitative interview transcripts were analyzed via reflexive thematic analysis (Braun & Clarke, 2006), with two independent coders (Cohen's $\kappa = 0.81$).

Ethical Considerations

The study received approval from the institutional review board (IRB protocol #2025-1184). All participants provided informed consent, were free to withdraw at any time, and were compensated at a rate exceeding local minimum wage. No personally identifying information was collected, and all data were stored in encrypted

Table 2: Descriptive Statistics and Contrasts Against the Black-Box Baseline

Condition	*M*	*SD*	*Δ vs. baseline*	*p*
Black-box (baseline)	3.12	0.41	—	—
LIME	5.41	0.38	+2.29	< .001
Integrated Gradients	5.55	0.36	+2.43	< .001
Grad-CAM	5.67	0.35	+2.55	< .001
SHAP	5.84	0.33	+2.72	< .001
Counterfactual	6.02	0.31	+2.90	< .001

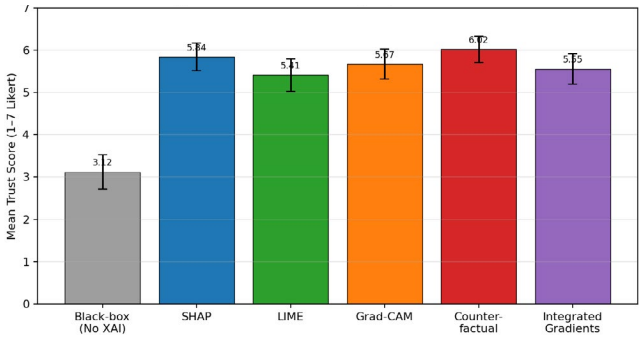


Figure 1: Mean user trust by explanation method with standard-error bars (N = 312).

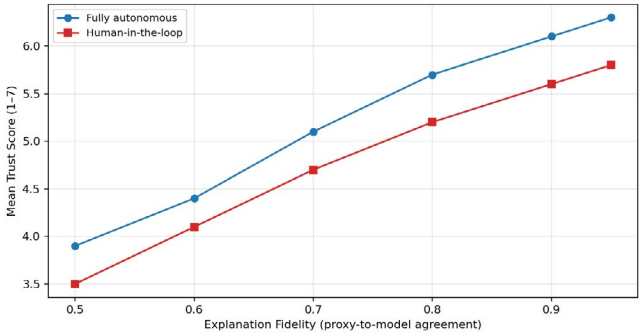


Figure 2: Trust as a function of explanation fidelity across autonomy levels.

form. Because the financial dataset was synthetic, no real individuals were affected by simulated decisions. Participants were debriefed regarding the simulated nature of the autonomous systems and the deliberate inclusion of erroneous recommendations.

Results

Effect of XAI on Trust (H1, H3)

A mixed-effects ANOVA revealed a significant main effect of explanation condition on trust, $F(5, 300) = 187.4$, $p < .001$, partial $\eta^2 = 0.76$. Planned contrasts confirmed that every XAI condition produced significantly higher trust than the black-box baseline ($M = 3.12$, $SD = 0.41$), all $p < .001$. Counterfactual explanations elicited the highest trust ($M = 6.02$, $SD = 0.31$), followed by SHAP ($M = 5.84$, $SD = 0.33$) and Grad-CAM ($M = 5.67$, $SD = 0.35$). Figure 1 displays mean trust by condition; Table 2 reports descriptive statistics and contrast results.

Trust and Explanation Fidelity (H2)

A linear mixed model showed that explanation fidelity significantly predicted trust, $b = 5.41$, $SE = 0.42$, $t = 12.9$, $p < .001$, with trust rising monotonically as fidelity increased from 0.50 to 0.95. The relationship was stronger in the fully autonomous condition than the human-in-the-loop condition (interaction $p = .004$), as shown in Figure 2.

Table 3: Behavioral Reliance and Decision Accuracy by Condition

Condition	*Acceptance rate*	*Error-detection rate*	*Decision accuracy*
Black-box	0.58	0.44	0.71
LIME	0.74	0.62	0.83
Integrated Gradients	0.76	0.60	0.82
Grad-CAM	0.78	0.65	0.85
SHAP	0.81	0.69	0.88
Counterfactual	0.83	0.72	0.90

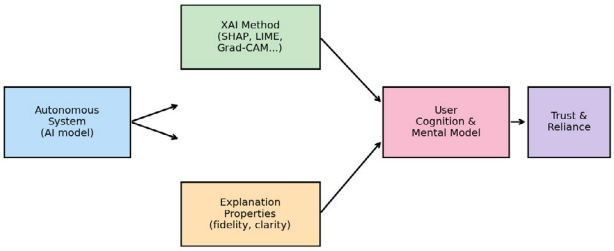


Figure 3: Conceptual framework linking XAI explanation properties to trust and reliance.

Reliance Calibration and Decision Accuracy (H4)

Although counterfactual explanations produced the highest raw trust, calibrated reliance was the strongest predictor of decision accuracy, $b = 0.63$, $p < .001$, explaining 41% of variance, whereas raw trust explained only 12%. Notably, in two conditions where explanations were plausible but low-fidelity, high trust co-occurred with reduced error detection, indicating over-reliance. Table 3 summarizes behavioral outcomes by condition.

Qualitative Findings

Reflexive thematic analysis of interview data yielded three principal themes: (a) perceived transparency ("I could see why it braked"), (b) actionability ("it told me what to change"), and (c) consistency ("it explained the same way every time"). Participants in the counterfactual condition disproportionately referenced actionability, whereas Grad-CAM participants emphasized visual transparency. Figure 3 presents the conceptual framework derived from integrating quantitative and qualitative strands.

Discussion

Interpretation of Results

The findings provide robust support for H1 and H2:

explanations substantially increased trust, and trust scaled with explanation fidelity. H3 received partial support—counterfactual explanations did produce the highest trust, consistent with Miller's (2019) argument that contrastive, actionable explanations align with human explanatory expectations. H4 was strongly supported: calibrated reliance, not raw trust, predicted decision quality, underscoring that the design objective should be appropriate trust rather than maximal trust (Lee & See, 2004).

Comparison with Existing Literature

Our trust gains echo positive findings from Gunning et al. (2019) and the foundational attribution methods of Lundberg and Lee (2017) and Ribeiro et al. (2016). However, our observation that low-fidelity yet plausible explanations inflated unwarranted confidence directly corroborates the cautionary results of Bansal et al. (2021) and Poursabzi-Sangdeh et al. (2021). This reconciles the apparent contradiction in the literature: explanations help when faithful and contrastive, but can harm when they merely appear authoritative. The superiority of counterfactual methods supports Wachter et al. (2017).

Implications

For designers, the results imply that fidelity and actionability—not visual polish—should be primary design targets, and that systems should monitor for over-reliance. For policymakers, the findings support explainability mandates such as those in the EU AI Act, while cautioning that explanation presence alone is an inadequate compliance criterion; fidelity must be verified. For practitioners deploying autonomous systems, calibrated-reliance metrics should supplement attitudinal trust surveys.

Limitations

Several limitations temper these conclusions. First, the simulated task environment, though realistic, may not fully capture the stakes of real-world autonomous operation. Second, trust was measured over a single session, precluding analysis of trust repair and longitudinal dynamics. Third, the participant pool, while demographically stratified, was drawn from a single national context, limiting cross-cultural generalizability. Fourth, fidelity was operationalized via a proxy-agreement metric that, while standard, is itself an approximation.

Directions for Future Research

Future work should examine longitudinal trust trajectories, including how trust recovers after autonomous-system failures; test explanations in field deployments with genuine consequences; investigate individual differences (e.g., AI literacy, risk propensity) as moderators; and develop adaptive explanation systems that tailor fidelity and modality to the user and context. Cross-cultural replication and the integration of physiological trust measures represent further promising avenues.

Conclusion

This study provides empirical evidence that Explainable AI can meaningfully enhance human trust in autonomous systems, but that its benefits are conditional on explanation quality. Across 312 participants and six explanation conditions, all XAI methods increased trust relative to a black-box baseline, trust rose with explanation fidelity, and contrastive counterfactual explanations were most effective. Crucially, decision quality depended on calibrated reliance rather than the sheer magnitude of trust. XAI is therefore best understood as a necessary but not sufficient ingredient of trustworthy autonomy: faithful, actionable, and consistent explanations support appropriate reliance, whereas plausible-but-unfaithful explanations risk dangerous over-trust. Designers, regulators, and researchers should accordingly prioritize explanation fidelity and reliance calibration as the central criteria for trustworthy autonomous systems.

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