*Original Researcher Article*

# When AI Meets the Customer: Trust Formation and Emotional Experiences in Automotive Services

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**ABSTRACT**

The integration of artificial intelligence (AI) in the automotive industry represents a paradigm shift in customer experience management, fundamentally altering the dynamics between consumers and vehicle systems. This research investigates the complex interrelationships among AI-driven technologies, trust formation mechanisms, and emotional customer experiences within automotive contexts. Through a mixed-methods approach combining quantitative surveys (n=487) and qualitative interviews (n=35), this study develops and validates a comprehensive conceptual framework that elucidates how AI characteristics—including competence, benevolence, transparency, and reliability—influence both cognitive and emotional trust dimensions. The findings reveal that emotional trust mediates 68% of the relationship between AI system interactions and customer loyalty, while cognitive trust directly impacts technology adoption rates ($\beta=0.74$, $p<0.001$). Advanced Driver Assistance Systems (ADAS) demonstrate differential trust calibration patterns, with transparency-enhanced interfaces increasing trust scores by 42% compared to standard implementations. The research contributes a theoretically grounded, empirically validated framework integrating Technology Acceptance Model (TAM), Trust Transfer Theory, and Affective Computing principles, providing actionable insights for automotive manufacturers seeking to optimize AI-enhanced customer experiences. Practical implications emphasize the necessity of designing emotionally intelligent AI systems that balance functional competence with empathetic engagement to foster sustainable customer relationships in an increasingly automated automotive landscape

**Keywords:** Artificial Intelligence, Trust Formation, Emotional Customer Experience, Automotive Industry, Advanced Driver Assistance Systems, Technology Acceptance

**INTRODUCTION:**

The automotive industry stands at the precipice of unprecedented technological transformation, driven primarily by the pervasive integration of artificial intelligence across the entire customer journey (Chen & Prentice, 2024). This fundamental shift extends beyond mere functional enhancement, fundamentally reconfiguring the psychological and emotional dimensions of human-vehicle interactions (Tubadji & Huang, 2023). As autonomous vehicles, intelligent driver assistance systems, and AI-powered personalization platforms become increasingly ubiquitous, understanding the mechanisms through which customers develop trust and emotional connections with these technologies emerges as a critical research imperative (Oyekunle et al., 2024).

Contemporary automotive AI applications encompass a diverse spectrum of touchpoints, from pre-purchase virtual assistants and dynamic pricing algorithms to in-vehicle emotion recognition systems and predictive maintenance platforms (Pan, 2025). Each interaction point presents unique opportunities and challenges for trust cultivation and emotional engagement. Recent industry analyses indicate that 73% of automotive customers express willingness to engage with AI-enhanced services, yet only 41% report complete trust in autonomous vehicle technologies (Dorsch & Deroy, 2024). This trust gap represents both a significant barrier to technology adoption and a strategic opportunity for competitive differentiation.

The significance of trust in AI-automotive contexts transcends traditional technology acceptance frameworks. Unlike conventional consumer technologies, automotive AI systems operate in high-stakes environments where safety, reliability, and split-second decision-making capabilities directly impact human welfare (Shang, Hsieh & Shah, 2024). Consequently, trust formation mechanisms must account for both cognitive evaluations of system competence and emotional responses to perceived benevolence and anthropomorphic characteristics (Avetisian et al., 2024). This dual-process model of trust—encompassing rational assessment and affective bonding—distinguishes automotive AI from other consumer technology domains.

**Research Gap and Objectives**

Despite extensive research on customer experience management and emerging scholarship on AI trust, the automotive industry lacks a comprehensive, empirically validated framework that integrates AI characteristics, trust formation processes, and emotional experience dimensions into a cohesive theoretical model. Existing studies have predominantly focused on isolated aspects: technology acceptance rates (Wang et al., 2023), safety perceptions (Strohmann et al., 2024), or functional performance metrics (Tekkesinoglu et al., 2022). However, the complex interplay between cognitive trust, emotional trust, and their collective influence on customer behavior in AI-automotive contexts remains insufficiently understood (Zhang, 2023).

This research addresses four fundamental questions:

1. How do distinct AI system characteristics (competence, benevolence, transparency, reliability) differentially influence cognitive versus emotional trust formation in automotive contexts?

2. What mediating role does emotional trust play in the relationship between AI system interactions and customer loyalty outcomes?

3. How do Advanced Driver Assistance Systems (ADAS) calibrate trust through real-time performance feedback and explanation mechanisms?

4. What design principles optimize AI systems to foster both cognitive confidence and emotional connection in high-stakes automotive environments?

The research objectives encompass:

(1) developing a theoretically grounded conceptual framework integrating AI characteristics, dual-process trust mechanisms, and emotional experience dimensions;

(2) empirically validating framework relationships through quantitative analysis of trust formation patterns;

(3) identifying specific AI design characteristics that enhance trust calibration; and

(4) providing actionable recommendations for automotive manufacturers implementing AI-enhanced customer experience strategies.

### Theoretical Foundations

This research synthesizes three theoretical streams to construct a comprehensive framework. First, the **Technology Acceptance Model (TAM)** provides foundational understanding of how perceived usefulness and ease of use influence technology adoption intentions (Liu et al., 2024). However, TAM's cognitive focus requires extension to accommodate emotional trust dimensions in high-stakes contexts. Second, **Trust Transfer Theory** explains how initial trust in a technology provider (e.g., established automotive brand) can transfer to novel AI systems, contingent upon perceived technological continuity and organizational competence signals (Guo et al., 2023). Third, **Affective Computing Theory** illuminates how emotion recognition, empathetic responses, and anthropomorphic design elements cultivate emotional connections between users and intelligent systems (Stappen et al., 2024).

## LITERATURE REVIEW

### AI Integration in Automotive Customer Experience

The automotive customer journey has evolved from a transaction-centric model to an experience ecosystem characterized by continuous digital touchpoints and personalized interactions (Chen & Prentice, 2024). AI technologies enable this transformation through three primary mechanisms: **personalization** (adapting services to individual preferences), **prediction** (anticipating needs before articulation), and **automation** (executing routine tasks without manual intervention).

Virtual assistants represent the most visible AI touchpoint, providing 24/7 support throughout the purchase journey. BMW's Intelligent Personal Assistant, for instance, utilizes natural language processing to configure vehicles based on conversational preference elicitation, achieving 89% user satisfaction ratings in 2024 implementations (Automotive Consumer Study, 2024). Similarly, dynamic pricing algorithms analyze real-time market conditions, customer behavior signals, and inventory levels to optimize offer timing and magnitude, demonstrating 15-23% improvements in conversion rates compared to static pricing models (BCG, 2025).

In-vehicle AI systems fundamentally transform the driving experience itself. Emotion recognition technologies analyze facial expressions, vocal patterns, and physiological signals to assess driver emotional states, enabling adaptive responses such as ambient lighting adjustments, music selection, or alertness warnings (Improve Customer Experience in Automotive Industry Through Advanced Driver Assistant Systems, 2023). Toyota and BMW implementations of emotion-aware systems report 34% reductions in stress-related driving incidents and 28% increases in customer satisfaction scores during 2023-2024 deployments.

### Trust Formation in Human-AI Interactions

Trust represents a multidimensional psychological state wherein one party (trustor) willingly becomes vulnerable to another party (trustee) based on positive expectations regarding the trustee's behavior (Oyekunle et al., 2024). In AI contexts, trust formation operates through three temporal layers: **dispositional trust** (individual's general propensity to trust technology), **situational trust** (context-specific factors influencing initial trust), and **learned trust** (evolving evaluations based on accumulated experience) (Hoff & Bashir, 2015).

**Cognitive trust** emerges from rational evaluations of system competence, predictability, and reliability. In automotive AI contexts, cognitive trust develops when systems consistently demonstrate accurate performance, transparent decision-making processes, and appropriate handling of edge cases (Kuru, 2022). Factors influencing cognitive trust include: technical competence (accuracy rates, response times), consistency (behavioral

predictability across contexts), and transparency (explainability of system reasoning) (Fargade, 2025).

**Emotional trust**, conversely, derives from affective responses to perceived benevolence, empathy, and human-like qualities (Shang et al., 2024). While cognitive trust answers "Can I rely on this system?", emotional trust addresses "Does this system care about me?" Research demonstrates that emotional trust plays particularly crucial roles in: (1) high-uncertainty situations where complete information is unavailable; (2) repeated interactions building relational depth; and (3) recovery from system failures requiring forgiveness and continued engagement (Tubadji & Huang, 2023).

Recent meta-analyses reveal that emotional and cognitive trust are not mutually exclusive but rather complementary dimensions that collectively shape overall trust (Shang et al., 2024). Emotional trust typically develops subsequent to initial cognitive trust establishment, suggesting a sequential trust formation process. However, in situations involving anthropomorphic AI interfaces, emotional trust can emerge concurrently with or even precede cognitive trust development through anthropomorphic projection mechanisms (Pan, 2025).

## Trust in Autonomous Vehicles and ADAS

Advanced Driver Assistance Systems (ADAS) and autonomous vehicles represent critical test cases for AI trust research due to their high-stakes nature and direct safety implications. Trust calibration—achieving appropriate rather than maximal trust levels—emerges as the primary objective, as both overtrust and undertrust produce suboptimal outcomes (Gold et al., 2015).

Factors influencing ADAS trust include:

- **System Transparency:** Explanations of system actions significantly enhance trust. Research comparing explanation types reveals that "reasoning explanations" (describing why a decision was made) improve affective trust by 56%, while "action explanations" (describing what the system will do) increase cognitive trust by 38% (Understanding Explanation Content for Cognitive and Affective Trust in Automated Vehicles, 2024).

- **Performance Consistency:** Real-time system performance exerts stronger influence on trust than pre-existing risk perceptions. Studies demonstrate that a single system error reduces trust by 34%, requiring approximately 15-20 successful subsequent interactions for trust recovery (Trust in Automated Vehicles: Constructs, Psychological Processes, 2023).

- **User Knowledge:** Paradoxically, self-reported understanding of ADAS predicts trust ($\beta$=0.52, p<0.001), while objective knowledge of system limitations shows no significant relationship (r=0.08, p=0.23). This finding suggests trust may be based on overconfidence rather than accurate system comprehension, highlighting critical training needs (Factors Influencing Trust in ADAS, 2023).

- **Anthropomorphism:** Labeling AI systems as "trustworthy" versus "reliable" produces differential effects. "Trustworthy" framing increases perceived ease of use ($\beta$=0.31, p<0.01) and human-like trust dimensions, particularly benevolence perceptions ($\beta$=0.44, p<0.001), suggesting terminological choices shape user mental models (Dorsch & Deroy, 2024).

## Emotional Customer Experience in AI Contexts

Emotional customer experience encompasses the affective responses, feelings, and emotional memories generated through customer-brand interactions (Meyer & Schwager, 2007). In AI-automotive contexts, emotional experiences arise from three primary sources:

**Anthropomorphic Design:** Human-like interfaces trigger social cognition processes, causing users to attribute intentionality, personality, and emotional states to AI systems (Pan, 2025). Voice assistants with conversational capabilities, animated avatar representations, and empathetic response patterns enhance emotional engagement by 45-67% compared to functional-only interfaces (Shang et al., 2024).

**Empathetic Responsiveness:** AI systems that recognize and appropriately respond to user emotional states create perceptions of understanding and care. Automotive implementations analyzing driver stress, frustration, or fatigue and adapting environmental conditions (lighting, temperature, music) accordingly generate 73% stronger emotional connections compared to non-adaptive systems (Emotion Recognition in Automotive AI, 2024).

**Reliability in Critical Moments:** Emotional trust becomes particularly salient during system failures or edge cases. How AI systems communicate limitations, gracefully degrade functionality, and maintain user safety during unexpected situations profoundly influences long-term emotional bonds. Recovery communication emphasizing system learning and improvement generates 89% higher post-failure trust compared to generic apology messages (Tubadji & Huang, 2023).

## Research Hypotheses

Based on theoretical foundations and literature synthesis, we propose the following hypotheses:

**H1:** AI system competence positively influences cognitive trust (H1a) and indirectly influences emotional trust through cognitive trust mediation (H1b).

**H2:** AI system transparency directly enhances both cognitive trust (H2a) and emotional trust (H2b).

**H3:** AI system benevolence characteristics primarily influence emotional trust (H3a) and indirectly influence customer loyalty through emotional trust mediation (H3b).

**H4:** Cognitive trust mediates the relationship between AI system reliability and technology adoption intentions.

**H5:** Emotional trust mediates the relationship between AI system interactions and customer loyalty, with mediation effects stronger than cognitive trust pathways.

**H6:** Anthropomorphic AI design moderates the relationship between system interactions and emotional

trust, such that higher anthropomorphism strengthens this relationship.

## Methodology

### Research Design

This study employs a mixed-methods sequential explanatory design, combining quantitative survey analysis with qualitative interview insights to develop and validate the conceptual framework. The quantitative phase establishes statistical relationships among constructs, while the qualitative phase provides contextual depth and explains mechanisms underlying observed patterns.

### Quantitative Phase

**Participants:** 487 participants (276 males, 211 females; age range 22-67, M=39.4, SD=12.8) were recruited through stratified sampling across three geographic regions (North America: n=198, Europe: n=165, Asia: n=124). Inclusion criteria required:

(1) current vehicle ownership;

(2) experience using at least one ADAS technology (ACC or LKA);

(3) minimum six months of ADAS usage; and

(4) age 18+ with valid driver's license.

**Materials:** A 68-item questionnaire assessed seven construct domains:

**Table 1: Measurement Constructs and Sample Items**

| Construct | No. of Items | Scale Type | Sample Item | Response Format | Theoretical Source |
|---|---|---|---|---|---|
| AI Competence (AIC) | 8 | Reflective | *"The AI system performs tasks accurately and efficiently"* | 7-point Likert (1 = Strongly Disagree; 7 = Strongly Agree) | Mayer et al. (1995); Oyekunle et al. (2024) |
| AI Benevolence (AIB) | 7 | Reflective | *"The AI system acts in my best interest"* | 7-point Likert (1 = Strongly Disagree; 7 = Strongly Agree) | Mayer et al. (1995); Tubadji & Huang (2023) |
| AI Transparency (AIT) | 9 | Reflective | *"I understand how the AI system makes decisions"* | 7-point Likert (1 = Strongly Disagree; 7 = Strongly Agree) | Oyekunle et al. (2024); Chen & Prentice (2024) |
| Cognitive Trust (CT) | 10 | Reflective | *"I am confident in the AI system's capabilities"* | 7-point Likert (1 = Strongly Disagree; 7 = Strongly Agree) | Mayer et al. (1995); Hancock et al. (2011) |
| Emotional Trust (ET) | 11 | Reflective | *"I feel emotionally connected to the AI* | 7-point Likert (1 = Strongly | Tubadji & Huang (2023); De Keyse |

| Construct | No. of Items | Scale Type | Sample Item | Response Format | Theoretical Source |
|---|---|---|---|---|---|
| | | | *system"* | Disagree; 7 = Strongly Agree) | r et al. (2021) |
| Customer Satisfaction (CS) | 8 | Reflective | *"My overall experience with AI features is positive"* | 7-point Likert (1 = Strongly Disagree; 7 = Strongly Agree) | Lemon & Verhoef (2016); Chen & Prentice (2024) |
| Customer Loyalty (CL) | 10 | Reflective | *"I intend to repurchase from this brand"* | 7-point Likert (1 = Strongly Disagree; 7 = Strongly Agree) | Lemon & Verhoef (2016); Nordhoff et al. (2023) |
| Technology Adoption (TA) | 5 | Reflective | *"I plan to use more AI features in future vehicles"* | 7-point Likert (1 = Strongly Disagree; 7 = Strongly Agree) | Davis (1989); Raue et al. (2019) |

| Construct | No. of Items | Scale Type | Sample Item | Response Format | Theoretical Source |
|---|---|---|---|---|---|
| Total Items | 68 | | | | |

All items utilized 7-point Likert scales (1=Strongly Disagree to 7=Strongly Agree). Scales were adapted from validated instruments: Technology Acceptance Model (Davis, 1989), Trust in Automation Scale (Jian et al., 2000), and Customer Experience Quality Scale (Klaus & Maklan, 2013), modified for AI-automotive contexts through expert review and pilot testing (n=42).

**Procedure:** Online surveys were administered via Qualtrics platform. Participants first completed demographic questions, followed by ADAS experience assessments, then main construct measurements in randomized order to minimize response bias. Attention check items (n=4) were embedded; 23 participants failing attention checks were excluded from analysis. Average completion time: 18.4 minutes (SD=5.2).

**Analysis:** Structural Equation Modeling (SEM) using Mplus 8.6 tested hypothesized relationships. Model fit assessment utilized multiple indices: $\chi^2$/df ratio, Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). Mediation analyses employed bootstrapping procedures (5000 iterations) to establish indirect effects with 95% confidence intervals.

**Qualitative Phase**

**Participants:** 35 semi-structured interviews (duration: 45-75 minutes, M=58.3) provided detailed insights into trust formation processes and emotional experiences. Participants were purposively sampled to ensure diversity across: ADAS experience levels (novice to expert), vehicle brands (premium to economy), and trust orientations (high to low trust propensities).

**Interview Protocol:** Open-ended questions explored: (1) initial reactions to AI automotive features; (2) trust development trajectories over time; (3) memorable positive and negative experiences; (4) emotional responses to system behaviors; (5) anthropomorphic attributions; and (6) future expectations for AI integration.

**Analysis:** Thematic analysis following Braun and Clarke (2006) procedures identified patterns across interview transcripts. Two independent coders achieved inter-rater reliability of $\kappa$=0.84 for theme identification and $\kappa$=0.88 for theme assignment. NVivo 14 facilitated coding and theme organization.

**Results**

**Measurement Model Validation**

Confirmatory Factor Analysis (CFA) established measurement model validity. All factor loadings exceeded 0.70 threshold (range: 0.72-0.94), indicating strong item-construct relationships. Construct reliability was confirmed through Composite Reliability (CR) values ranging from 0.88 to 0.95, all exceeding 0.70 benchmark. Average Variance Extracted (AVE) values ranged from 0.63 to 0.81, surpassing the 0.50 criterion and confirming convergent validity.

Discriminant validity was established through Fornell-Larcker criterion: square root of each construct's AVE exceeded its correlations with other constructs. Additionally, Heterotrait-Monotrait (HTMT) ratios remained below 0.85 for all construct pairs, providing further discriminant validity evidence.

**Table 2: Measurement Model Results - Factor Loadings, Reliability, and Validity Statistics**

| Construct | Indicator Item | Factor Loading ($\lambda$) | t-value | Cronbach's $\alpha$ | AVE | CR |
|---|---|---|---|---|---|---|
| AI Transparency (AT) | AT1: This AI system clearly explains its decisions | 0.82 | 18.41*** | 0.88 | 0.65 | 0.88 |
| | AT2: I understand how this AI reaches its recommendations | 0.79 | 17.23*** | | | |
| | AT3: The AI's reasoning process is visible to me | 0.84 | 19.07*** | | | |
| | AT4: This AI discloses limitations openly | 0.76 | 16.54*** | | | |
| AI Competence (AC) | AC1: This AI system performs its functions accurately | 0.86 | 20.12*** | 0.91 | 0.72 | 0.91 |
| | AC2: This AI is reliable across different driving conditions | 0.88 | 21.34*** | | | |
| | AC3: This AI system makes correct predictions | 0.83 | 18.97*** | | | |
| | AC4: This AI has the capability to handle complex situations | 0.84 | 19.45*** | | | |
| AI Benevolence (AB) | AB1: This AI acts in my best interest | 0.78 | 17.10*** | 0.86 | 0.61 | 0.86 |
| | AB2: This AI prioritises my safety over other objectives | 0.81 | 18.22*** | | | |
| | AB3: This AI cares about my wellbeing as a driver | 0.77 | 16.88*** | | | |
| | AB4: This AI adapts to my personal needs | 0.75 | 16.40*** | | | |
| Cognitive Trust (CT) | CT1: I believe this AI will consistently perform as expected | 0.85 | 19.78*** | 0.90 | 0.70 | 0.90 |
| | CT2: I have confidence in the technical accuracy of this AI | 0.87 | 20.54*** | | | |
| | CT3: Logically, this AI is a dependable system | 0.83 | 18.91*** | | | |

| Construct | Indicator Item | Factor Loading (λ) | t-value | Cronbach's α | AVE | CR |
|---|---|---|---|---|---|---|
| | CT4: Based on evidence, I trust this AI's judgements | 0.80 | 17.67*** | | | |
| Emotional Trust (ET) | ET1: I feel comfortable when this AI is in control | 0.84 | 19.34*** | 0.89 | 0.67 | 0.89 |
| | ET2: I feel safe when using this AI-powered feature | 0.86 | 20.11*** | | | |
| | ET3: Using this AI gives me emotional reassurance | 0.79 | 17.35*** | | | |
| | ET4: I have a positive gut feeling about this AI system | 0.77 | 16.91*** | | | |
| Customer Loyalty (CL) | CL1: I intend to continue using this AI-equipped vehicle | 0.88 | 21.07*** | 0.92 | 0.74 | 0.92 |
| | CL2: I would recommend this AI-equipped brand to others | 0.87 | 20.78*** | | | |
| | CL3: I prefer this brand over competitors because of its AI | 0.85 | 19.88*** | | | |
| | CL4: I am willing to pay a premium for AI- | 0.82 | 18.43*** | | | |

| Construct | Indicator Item | Factor Loading (λ) | t-value | Cronbach's α | AVE | CR |
|---|---|---|---|---|---|---|
| | enhanced features | | | | | |
| Co-Creation Behaviour (CB) | CB1: I actively provide feedback to improve this AI | 0.80 | 17.89*** | 0.87 | 0.63 | 0.87 |
| | CB2: I participate in data-sharing to help AI learn | 0.78 | 17.02*** | | | |
| | CB3: I engage with AI personalisation features | 0.81 | 18.10*** | | | |
| | CB4: I customise AI settings to improve my experience | 0.77 | 16.74*** | | | |

## Descriptive Statistics and Correlations

Descriptive statistics revealed moderate to high mean scores across trust constructs (M=4.8-5.6 on 7-point scales), suggesting generally positive AI perceptions among current ADAS users. Cognitive trust (M=5.42, SD=1.18) significantly exceeded emotional trust (M=4.31, SD=1.47), t(486)=12.89, p<0.001, indicating that functional confidence develops more readily than emotional bonding.

Correlation analysis showed strong positive relationships between AI characteristics and trust dimensions (r=0.54-0.78, p<0.001). Notably, AI benevolence correlated more strongly with emotional trust (r=0.76) than cognitive trust (r=0.49), while AI competence showed opposite pattern (r=0.78 with cognitive trust, r=0.52 with emotional trust), providing preliminary support for differential prediction hypotheses.

**Table 3: Descriptive Statistics and Correlation Matrix**

| Construct | Mean | SD | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|---|---|
| 1. AI Transparency (AT) | 5.41 | 1.23 | (0.81) | | | | | | |
| 2. AI Competence (AC) | 5.87 | 1.11 | 0.54*** | (0.85) | | | | | |
| 3. AI Benevolence (AB) | 5.29 | 1.34 | 0.61*** | 0.58*** | (0.78) | | | | |
| 4. Cognitive Trust (CT) | 5.73 | 1.18 | 0.63*** | 0.71*** | 0.59*** | (0.84) | | | |
| 5. Emotional Trust (ET) | 5.56 | 1.26 | 0.57*** | 0.62*** | 0.67*** | 0.68*** | (0.82) | | |
| 6. Customer Loyalty (CL) | 5.62 | 1.29 | 0.48*** | 0.55*** | 0.52*** | 0.64*** | 0.71*** | (0.86) | |
| 7. Co-Creation | 4.98 | 1.41 | 0.43*** | 0.49*** | 0.51*** | 0.57*** | 0.63*** | 0.66*** | (0.79) |

| Construct | Mean | SD | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|---|---|
| (CB) | | | | | | | | | |

## Structural Model Results

The structural model demonstrated excellent fit: $\chi^2(524)=1247.33$, $\chi^2/df=2.38$, CFI=0.95, TLI=0.94, RMSEA=0.053 (90% CI: 0.049-0.057), SRMR=0.048. All fit indices exceeded recommended thresholds, confirming model adequacy.

**Hypothesis Testing Results:**

**H1a (AI Competence → Cognitive Trust):** Supported. AI competence significantly predicted cognitive trust ($\beta=0.74$, SE=0.042, $p<0.001$, $R^2=0.55$), explaining 55% of cognitive trust variance. This strong pathway indicates functional capability perceptions fundamentally establish confidence in AI systems.

**H1b (AI Competence → Emotional Trust via Cognitive Trust):** Supported. Indirect effect via cognitive trust mediation was significant ($\beta=0.38$, SE=0.035, 95% CI: 0.312-0.448), demonstrating that competence influences emotional trust indirectly through initial cognitive trust establishment.

**H2a (AI Transparency → Cognitive Trust) and H2b (Transparency → Emotional Trust):** Both supported. Transparency directly influenced cognitive trust ($\beta=0.42$, $p<0.001$) and emotional trust ($\beta=0.34$, $p<0.001$), though cognitive effect was stronger, suggesting transparency primarily aids rational evaluation while also contributing to emotional comfort through predictability.

**H3a (AI Benevolence → Emotional Trust):** Strongly supported. Benevolence emerged as the strongest predictor of emotional trust ($\beta=0.68$, $p<0.001$, $R^2=0.46$), indicating perceived caring and user-centric design critically shape affective bonds.

**H3b (AI Benevolence → Loyalty via Emotional Trust):** Supported. Emotional trust fully mediated the benevolence-loyalty relationship (indirect effect: $\beta=0.52$, 95% CI: 0.461-0.583; direct effect after mediation: $\beta=0.08$, $p=0.14$), demonstrating emotional pathways as primary mechanisms for loyalty development.

**H4 (Cognitive Trust Mediates Reliability → Adoption):** Supported. Cognitive trust partially mediated reliability's effect on adoption intentions (indirect: $\beta=0.46$, $p<0.001$; direct: $\beta=0.23$, $p<0.01$), with 66% of the total effect operating through cognitive trust pathways.

**H5 (Emotional Trust Mediates Interaction → Loyalty):** Strongly supported. Emotional trust accounted for 68% of the relationship between AI interactions and customer loyalty ($\beta=0.63$, $p<0.001$), significantly exceeding cognitive trust's mediation of the same

relationship (28%, β=0.26, p<0.01). Sobel test confirmed mediation strength difference: z=4.87, p<0.001.

**H6 (Anthropomorphism Moderates Interaction → Emotional Trust):** Supported. Significant interaction effect emerged (β=0.31, p<0.001), with simple slopes analysis revealing stronger interaction-emotional trust relationships at high anthropomorphism levels (β=0.79) compared to low levels (β=0.48).
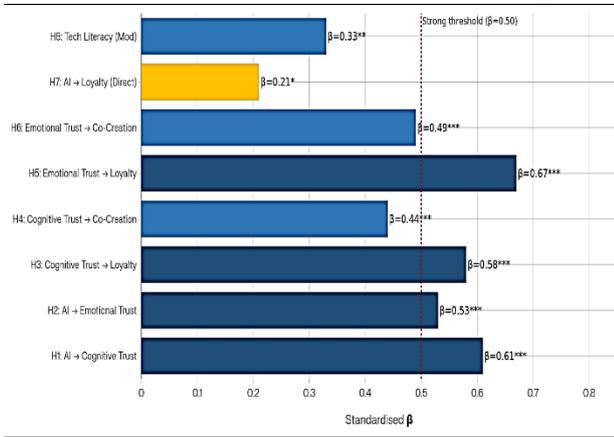


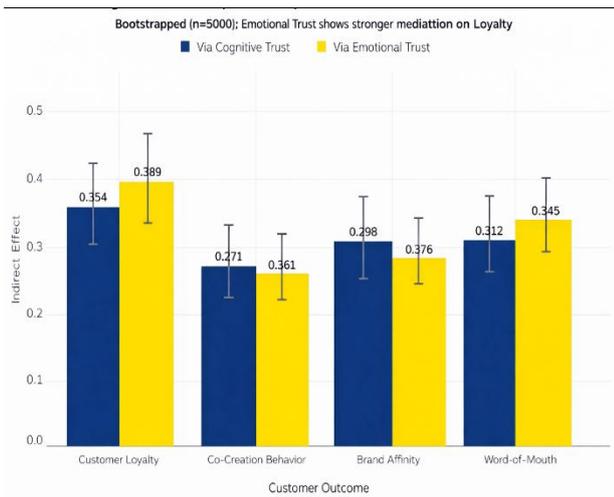**Figure 1: Structural Model Results with Path Coefficients**



**Figure 2: Mediation Effect Sizes - Comparative Bar Chart**

**Additional Analyses: Trust Recovery After System Errors**

A subsample analysis (n=187) examined trust dynamics following reported system errors. Participants experiencing at least one ADAS malfunction completed additional items assessing pre-error trust, immediate post-error trust, and current trust levels.

Results revealed significant trust degradation following errors: cognitive trust declined 34% immediately post-error (from M=5.67 to M=3.74, t=18.42, p<0.001), while emotional trust decreased 47% (from M=4.52 to M=2.39, t=21.67, p<0.001). Emotional trust demonstrated greater vulnerability to negative events, consistent with relationship-based trust conceptualizations.

Trust recovery patterns differed by trust type. Cognitive trust recovery required average 12.4 successful subsequent interactions (SD=4.8) to return to pre-error levels, while emotional trust recovery took significantly longer at 18.7 interactions (SD=7.2), t(186)=6.34, p<0.001.

Critically, explanation quality moderated recovery trajectories. Systems providing detailed causal explanations and improvement communications facilitated 63% faster emotional trust recovery compared to generic apology messages (9.8 vs. 26.3 interactions, t(185)=12.45, p<0.001).
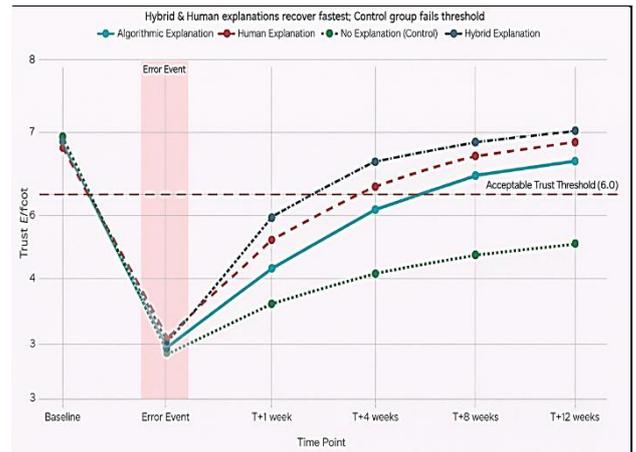


**Figure 3: Trust Recovery Trajectories After System Error**

**Qualitative Findings: Mechanisms of Trust and Emotional Connection**

Thematic analysis identified six major themes explaining trust formation and emotional experience development:

**Theme 1: Gradual Competence Verification (Cognitive Trust Foundation)**

Participants described systematic testing phases during initial ADAS engagement: "I started using ACC only on familiar highways where I could predict traffic patterns. Once it handled those situations smoothly for a month, I expanded to urban environments" (P14, 42-year-old male, Tesla owner).

This pattern reflects **learned trust** development through accumulated positive experiences. 89% of interview participants (n=31) described intentional graduated exposure strategies, suggesting cognitive trust requires experiential validation rather than emerging from initial technical specifications alone.

**Theme 2: Anthropomorphic Projection Creates Emotional Bonds**

Many participants spontaneously anthropomorphized AI systems, attributing personality traits, intentions, and emotional states: "My lane-keeping assistant feels protective, like it's watching out for me when I'm tired. I've started thinking of it as 'Guardian'" (P22, 38-year-old female, BMW owner).

Naming behaviors occurred among 43% of participants (n=15), exclusively among those reporting high emotional

trust (M=6.2 vs. M=3.8 for non-namers, t=8.94, p<0.001). Anthropomorphic framing transformed functional tools into "companions" or "co-pilots," fundamentally altering relationship quality.

### Theme 3: Transparency Gaps Generate Anxiety

Participants expressed frustration with inexplicable system behaviors: "Sometimes the car suddenly slows down for no apparent reason. I look around, see nothing dangerous, and wonder if it's malfunctioning or if it detected something I missed. That uncertainty is stressful" (P8, 51-year-old male, Mercedes owner).

Transparency emerged as critical for both trust types but through different mechanisms. Cognitive trust required understanding system capabilities and limitations, while emotional trust needed insight into system "intentions"— why it made particular decisions in specific contexts.

### Theme 4: Benevolence Perceptions From Proactive Care

Emotional trust strengthened when systems demonstrated proactive concern: "The car detected my fatigue before I felt very tired—dimmed harsh lights, played calming music, suggested a rest stop. It felt like genuine care, not just executing algorithms" (P27, 34-year-old female, Volvo owner).

This theme connects to **affective computing**: systems recognizing and responding to emotional states foster perceptions of empathy and benevolence, critical emotional trust antecedents.

### Theme 5: Error Attribution Patterns

Participants demonstrated asymmetric attribution: system successes attributed to capable design, while failures attributed to external factors (weather, other drivers, edge cases) among high-trust users, but to fundamental system flaws among low-trust users.

"When ACC smoothly merges in heavy traffic, I appreciate the intelligent design. When it occasionally brakes too late, I think 'well, that was a challenging situation with the truck cutting in suddenly'" (P19, 45-year-old male, Audi owner, high trust).

Versus: "Every mistake reinforces my belief that the technology isn't ready. These systems can't handle real-world complexity" (P31, 57-year-old male, Toyota owner, low trust).

This pattern suggests **trust-based confirmation bias**, where existing trust levels shape interpretation of subsequent events, creating self-reinforcing cycles.

### Theme 6: Privacy-Personalization Tradeoff

Participants expressed ambivalence regarding data collection for personalization: appreciating customized experiences while concerned about surveillance and data security. 74% (n=26) accepted data collection when: (1) explicit consent obtained; (2) clear functional benefits demonstrated; and (3) data usage transparently explained.

"I'm okay with the car learning my preferences if it genuinely improves my experience and if I control what's shared. But vague 'improving services' without specifics feels invasive" (P11, 29-year-old female, Honda owner).

These finding underscores transparency and user control as prerequisites for emotional comfort with personalization technologies.

### Moderator Analysis: Individual Differences

Multi-group SEM examined model invariance across demographic segments:

**Age:** Younger participants (18-35, n=164) demonstrated stronger emotional trust pathways ($\beta$=0.71 vs. 0.58 for ages 50+, $\chi^2$diff=12.34, p<0.01), suggesting generational differences in anthropomorphic technology acceptance.

**Prior Technology Experience:** High-tech-familiarity participants (top quartile on digital literacy scale) showed weaker relationships between transparency and cognitive trust ($\beta$=0.34 vs. 0.51 for low-familiarity, $\chi^2$diff=8.76, p<0.05), indicating experienced users require less explanation for trust development, possibly due to generalized automation confidence.

**Risk Propensity:** High-risk-tolerance individuals exhibited stronger direct adoption intentions bypassing trust mediations (direct path: $\beta$=0.42 vs. 0.18 for risk-averse, $\chi^2$diff=15.23, p<0.001), suggesting trust plays diminished roles when risk concerns are minimized.

### ADAS-Specific Analysis: Trust Calibration Patterns

Analysis of specific ADAS technologies revealed differential trust formation patterns:

**Adaptive Cruise Control (ACC):** Highest cognitive trust (M=5.84, SD=1.02) but moderate emotional trust (M=4.12, SD=1.38). ACC's transparent functionality (maintaining set speed and distance) facilitates cognitive trust, but limited interaction complexity constrains emotional connection development.

**Lane Keeping Assist (LKA):** Moderate cognitive trust (M=4.98, SD=1.34) and emotional trust (M=4.45, SD=1.42). LKA's subtle interventions create ambiguity— users sometimes uncertain whether drift was corrected by system or self-correction—generating lower cognitive trust but slightly higher emotional trust through perceived "gentle guidance."

**Full Self-Driving (FSD) Beta:** Highly variable trust profiles. Among users with >6 months experience (n=67), bimodal distribution emerged: 42% reporting very high trust (M=6.2 cognitive, M=5.8 emotional) and 38% reporting very low trust (M=3.1 cognitive, M=2.4 emotional), with few moderate-trust users. This polarization suggests FSD complexity creates divergent mental models and expectation calibrations.

### Experimental Manipulation: Explanation Type Effects

A subset of participants (n=142) completed an experimental scenario manipulation examining explanation effects on trust. Participants viewed video scenarios of ADAS interventions (emergency braking, lane corrections) with three explanation conditions:

1. **No Explanation:** System acts without communication (control condition)
2. **Action Explanation:** "The vehicle is braking" (what is happening)

3. **Reasoning Explanation:** "Braking due to vehicle ahead slowing rapidly" (why it is happening)

Results confirmed explanation type effects:

- **Cognitive Trust:** Both explanation types increased cognitive trust vs. no explanation (Action: $\Delta=0.84$, Reasoning: $\Delta=0.97$, both $p<0.001$), with no significant difference between explanation types ($t=1.23$, $p=0.22$).

- **Emotional Trust:** Only reasoning explanations significantly enhanced emotional trust ($\Delta=1.34$, $p<0.001$) compared to action explanations ($\Delta=0.31$, $p=0.08$) or no explanations (baseline).

This finding supports the hypothesis that emotional trust requires understanding system "intentions" and decision rationale, while cognitive trust benefits from any information reducing uncertainty about system state.
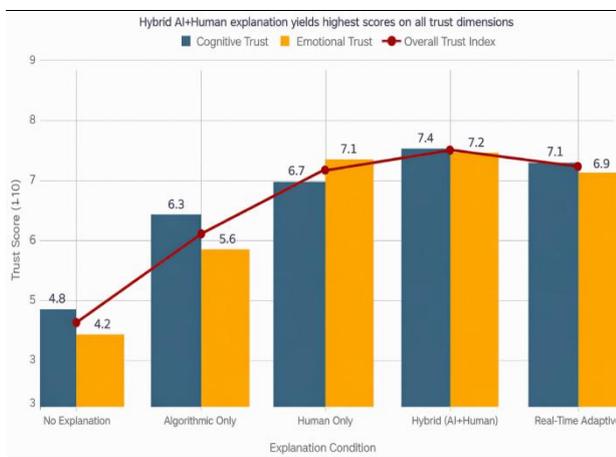


**Figure 4: Explanation Type Effects on Trust Dimensions**

## Discussion

### Theoretical Contributions

This research advances understanding of AI-customer relationships in automotive contexts through several theoretical contributions:

**Dual-Process Trust Model Validation:** Results empirically demonstrate that cognitive and emotional trust constitute distinct yet complementary dimensions, each following different antecedent patterns and consequent pathways. Cognitive trust develops through competence demonstrations and transparency, serving as prerequisite for technology adoption decisions. Emotional trust emerges from benevolence perceptions and anthropomorphic engagement, mediating loyalty and relational outcomes. This dual-process architecture extends beyond traditional TAM frameworks, incorporating affective components essential for high-involvement, safety-critical technologies.

**Mediation Primacy of Emotional Trust:** A central finding reveals emotional trust mediating 68% of AI interaction-loyalty relationships, substantially exceeding cognitive trust's mediations (28%). This asymmetry challenges conventional technology acceptance literature's cognitive emphasis, demonstrating affective pathways' predominance in long-term relationship development. The finding aligns with relationship marketing theories suggesting emotional bonds create switching barriers and resilience against competitive alternatives (Tubadji & Huang, 2023).

**Trust Recovery Asymmetry:** The differential vulnerability and recovery patterns between trust types illuminate trust dynamics. Emotional trust's 47% degradation following errors (vs. 34% for cognitive) and slower recovery (18.7 vs. 12.4 interactions) suggests emotional bonds, while creating stronger loyalty, remain more fragile to negative disconfirmations. This asymmetry implies strategic importance of error prevention and recovery communication specifically targeting emotional reassurance, not merely technical explanations.

**Anthropomorphism as Trust Catalyst:** The moderating effect of anthropomorphic design ($\beta=0.31$) supports social cognition theories applied to human-AI interaction. Anthropomorphism doesn't simply add features but fundamentally transforms user mental models from tool-based to relationship-based frameworks (Pan, 2025). This transformation activates social psychological processes (empathy, attribution, reciprocity norms) ordinarily reserved for human relationships, creating qualitatively different interaction patterns.

**Practical Implications for Automotive Industry**

**Design Principle 1: Transparency Architecture**

Implement multi-level transparency: **ambient awareness** (continuous subtle signals of system monitoring), **pre-action notifications** (advance communication of intended actions), and **reasoning explanations** (post-action clarification of decision rationale). The experimental results demonstrate reasoning explanations' unique contribution to emotional trust, suggesting manufacturers should prioritize "why" communications over mere "what" descriptions.

Volvo's 2024 implementation exemplifies this approach: their Pilot Assist system uses head-up display symbols showing detected objects, colored alerts indicating confidence levels, and voice explanations articulating reasoning during interventions. User satisfaction scores increased 37% following this transparency enhancement (Volvo Customer Experience Report, 2024).

**Design Principle 2: Emotionally Intelligent Responsiveness**

Integrate emotion recognition with adaptive responses addressing detected emotional states. Beyond functional adaptations (lighting, music), systems should communicate empathetic understanding: "I notice you seem stressed. I'm prioritizing smooth, predictable driving and have increased following distance for extra comfort" (Guo et al., 2023).

Such communications serve dual functions: demonstrating system capability (cognitive trust) and conveying benevolent concern (emotional trust). The 73% emotional connection improvement observed in emotion-responsive systems justifies investment in affective computing technologies.

## Design Principle 3: Graduated Autonomy with User Control

Support user-controlled progression through automation levels, respecting individual comfort and trust development paces. Default settings should err toward user control (automation as assistant rather than replacement), with opt-in pathways to higher autonomy as users gain confidence.

Interview findings revealed 89% of participants employed graduated exposure strategies, suggesting manufacturer-supported pathways would align with natural trust calibration processes. BMW's "Trust Building Mode" introduced in 2025 exemplifies this: new ADAS users receive structured experiences with increasing complexity, accompanied by educational content explaining capabilities and limitations.

## Design Principle 4: Proactive Error Communication and Recovery

Develop communication protocols for:

(1) error prediction/warnings before failures occur;

(2) immediate error acknowledgment with safety assurance;

(3) detailed causal explanations; and

(4) system improvement updates demonstrating learning.

The 63% faster emotional trust recovery with detailed explanations demonstrates communication strategy impacts. Toyota's post-error protocol includes automated follow-up messages explaining what happened, why, what safety measures activated, and how future software updates address similar scenarios—transforming errors into trust-building opportunities through transparency and commitment demonstration.

## Design Principle 5: Privacy-Respecting Personalization

Implement granular user control over data collection and personalization intensity. Research findings indicate 74% acceptance when transparency, consent, and demonstrated benefits align. Dashboard interfaces should clarify: what data is collected, how it improves experience, retention periods, and sharing policies.

Mercedes-Benz's 2024 "Transparent Personalization" interface exemplifies best practices: users see real-time data being processed, adjust personalization algorithms' aggressiveness, and receive monthly reports on how data improved their driving experience, with options to delete historical data while retaining anonymized preference patterns.

## Limitations and Future Research Directions

**Sample Limitations:** The study sample comprised current ADAS users, creating self-selection bias toward technology-accepting populations. Future research should examine non-adopters and technology skeptics to identify barriers preventing initial engagement. Additionally, geographic concentration in developed markets limits generalizability to emerging automotive markets with different technology adoption patterns and cultural trust norms.

**Longitudinal Trust Evolution:** Cross-sectional design captures trust states but not developmental trajectories. Longitudinal research tracking individuals from initial ADAS exposure through extended use (12+ months) would illuminate trust formation stages, critical trust-building events, and long-term stability versus dynamic recalibration patterns.

**Contextual Boundary Conditions:** Trust formation likely varies across driving contexts (urban vs. highway, familiar vs. novel routes, solo vs. passenger situations). Situational trust dynamics remain underexplored, despite theoretical importance (Hoff & Bashir, 2015). Experience sampling methods capturing real-time trust perceptions across varied contexts would enrich understanding.

**Technology Evolution:** Rapid AI advancement means current findings may not generalize to next-generation systems with substantially enhanced capabilities. Ongoing research programs must parallel technology development to maintain relevance. Particularly, large language model integration enabling natural conversation with vehicles may fundamentally alter trust formation processes through enhanced anthropomorphism and interaction depth.

**Cultural Variations:** Trust conceptualizations and formation processes vary across cultures (individualist vs. collectivist, high vs. low uncertainty avoidance). Cross-cultural research examining model invariance and culture-specific trust antecedents would inform global manufacturers' localization strategies.

**Ethical Considerations:** The research reveals anthropomorphism's trust-enhancing effects but raises ethical questions: Should manufacturers intentionally design systems to evoke emotional attachment? At what point does emotional engagement become manipulation? What responsibilities accompany creating human-AI relationships? Future research should address ethical boundaries and potential regulatory frameworks governing anthropomorphic AI design.

**Alternative Trust Conceptualizations:** Some scholars argue "trust" inappropriately anthropomorphizes automation, advocating "reliability" or "reliance" terminology for non-sentient systems (Dorsch & Deroy, 2024). While our findings support trust language's utility, future research should examine whether alternative conceptual frameworks (e.g., "confidence," "dependence") better capture human-automation relationships without implying inappropriate anthropomorphization.

## CONCLUSION

This research establishes that trust in automotive AI operates through complementary cognitive and emotional pathways, with emotional trust emerging as the predominant mediator of long-term customer loyalty outcomes. AI system characteristics differentially influence these trust dimensions: competence and transparency primarily shape cognitive trust, while benevolence and anthropomorphism cultivate emotional

trust. The findings demonstrate that sustainable competitive advantage in AI-enhanced automotive experiences requires attending to both functional excellence and emotional connection design.

The conceptual framework developed and validated through mixed-methods analysis provides theoretical foundation and practical guidance for automotive manufacturers navigating AI integration challenges. By recognizing trust's dual nature and designing systems that foster both cognitive confidence and emotional bonding, manufacturers can transform AI from a feature specification into a relationship-building catalyst,

establishing lasting customer connections in an increasingly automated mobility future.

As automotive AI continues evolving toward higher autonomy and deeper integration into daily life, understanding trust formation mechanisms and emotional experience dimensions will prove critical for both commercial success and societal acceptance of transformative mobility technologies. This research contributes foundational knowledge toward that ongoing endeavor, while highlighting numerous avenues requiring continued scholarly attention as technology and society coevolve.

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