



# *Shaping Trust Through System Design: Human Perceptions of AI in Design Ideation*

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# AI Becomes a Cognitive Collaborator in Engineering Design

## Introduction & Motivation

### ■ **AI is Transforming How We Work**

- Recent advancements in Artificial Intelligence (AI) have transformed how people seek information, solve problems, and even develop social relationships <sup>[1,2]</sup>.

### ■ **Integration in Engineering Design**

- AI has been integrated across the design process, from need finding <sup>[3,4]</sup>, brainstorming <sup>[5,6]</sup>, and concept generation <sup>[6–11]</sup> to design evaluation <sup>[12–15]</sup>, prototyping <sup>[16]</sup>, as well as design education <sup>[17]</sup>.

### ■ **A Shift in Paradigm: AI as a Collaborator**

- Attention is now being paid to how AI systems can augment human creativity as cognitive collaborators, particularly in early-stage design <sup>[18–21]</sup>.

# Trust Drives Engagement and Creativity

## Background

- **Trust** has emerged as a key influencing factor of human-AI collaboration [22–24].
  - It shapes users' willingness to accept suggestions and rely on system input, especially in creative domains where there may be no clear right answer [2,25,26].
- Trust in AI is not a fixed trait, but a dynamic construct influenced by system behaviors and individual user characteristics [27,28].
- There is **limited insight** into which specific design attributes effectively support user trust, user engagement, and creativity *from a systematic perspective*.

# From Disposition to Design: How Trust Is Formed

## Background

- Trust can be categorized as dispositional, situational, and learned trust [25-27].
- Three design attributes have been widely linked to trust formation.
  - **Appearance** enhances social presence and approachability [29-31]
  - **Performance** reinforces trust in the system's capabilities [29,30,32]
  - **Empathetic Behavior** fosters emotional connections via the affective process of decision-making [28,33-37]



# Research Questions and Hypotheses

- How do AI system design attributes influence user trust in creative design tasks?
- We hypothesize that high levels of these attributes will lead to greater user trust compared to low levels.
  - **H1a:** A human-like **appearance** increases trust.
  - **H1b:** High **performance** (detailed explanation) increases trust.
  - **H1c: Empathetic behavior** increases trust.
- Which design attributes are relatively more important in shaping trust, and is any attribute valued more than the others?

# Introducing AIDA: The AI Design Assistant

Method: System Design

**AIDA**

**Artificial  
Intelligence  
Design  
Assistant**



A newly designed conversational AI system supports early-stage design ideation.



It fills a gap in domain-specific tools for novice designers by offering interactive critique and feedback through natural dialogue.



Its modular architecture enables systematic testing of different chatbot design variations to assess their impact on user experience and ideation outcomes.

# Building AIDA: An Evolutionary Approach

## Method: System Development

- The development of AIDA followed an evolutionary model to build its capabilities progressively.

### Phase 1: Baseline Model Development

Utilized a fine-tuned RoBERTa model trained on 672 design ideas for sustainable washing machines from a previous ideation study <sup>[76]</sup>.

### Phase 2: Integration of Modern LLMs

Integrated GPT-4o (OpenAI) and LLaMA3 (Meta) as foundational models for rich, multi-turn conversational understanding.

### Phase 3: Adaptive Conversation Management

Focused on conversation design and full session memory, enabling fully adaptive interactions tailored to the ongoing context.

# Building AIDA: System Components & Phase Capabilities

Method: System Development

- **Conversational interface layer:**  
Responsive React-based chat interface
- **Cognitive processing engine:**  
Asynchronous Python backend with FastAPI
- **Evaluation framework:**  
Scoring modules powered by LLMs
- **Knowledge integration system:**  
Context-aware mechanism embedding design principles

CAPABILITY	Phase 1	Phase 2	Phase 3 (Current)
Evaluation accuracy	Moderate	High	Very High
Contextual awareness	Limited	Moderate	Excellent
Dialogue adaptability	Static	Semi-adaptive	Fully adaptive
Interaction style	One-size-fits-all	Personalized	Multi-version
Criteria application	Independent	Integrated	Contextual



# Building AIDA: Evaluation Framework

Method: System Development

- AIDA assesses user-generated ideas on three key criteria using criteria-guided prompting:

## Novelty

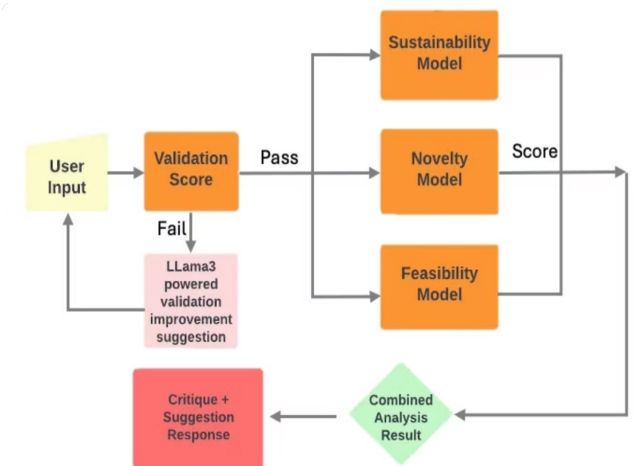
- Uniqueness
- Innovation
- Technological advances
- User experience
- Environmental impact

## Feasibility

- Technical feasibility
- Scalability
- User adoption
- Integration with existing systems

## Sustainability

- Environmental impact
- Economic impact
- Resource efficiency
- Long-term viability



# Designing AIDA: Manipulating Design Attributes

## Method: System Design

- Four distinct system versions were created with three attributes and two levels of each, to balance variation while minimizing participant fatigue.

Version	Appearance	Performance	Empathy
V1	Human	High	Empathetic
V2	Icon	High	Non-Empathetic
V3	Human	Low	Non-Empathetic
V4	Icon	Low	Empathetic

- Appearance**

- **High:** A human-like avatar with a professional look to enhance communication and promote social presence [38,39].
- **Low:** An abstract icon highlighting a computational aspect.



# Designing AIDA: Manipulating Design Attributes

Method: System Design

## ■ Performance

### High Level: Detailed Feedback

**Critique:** *"The description of a washing machine with an integrated AI system that customizes washing cycles is not entirely novel, as similar systems already exist in the market. However, the integration of AI to analyze fabric type and load size could be an innovation. In terms of feasibility, while the technology exists, there are concerns about user acceptance, scalability, and integration with existing systems. The lack of details on how the AI system will work and its potential limitations may also impact feasibility."*

### Suggestion for Improvement:

- **Novelty:** *Emphasize the specific advantages of the AI-powered washing machine, such as improved fabric protection or energy efficiency. Highlight how the customization features can cater to specific user needs (e.g., users with sensitive fabrics).*
- **Feasibility:** *.....*

### Low Level: General Feedback

**Critique:** *"While the concept of a washing machine with AI-powered customization is novel, it's not particularly innovative or technologically advanced, as similar solutions already exist in the market."*

**Suggestion:** *"To improve novelty, consider integrating more cutting-edge technologies, such as IoT sensors and machine learning algorithms, to create a truly unique user experience. This could include features like predictive maintenance, automated fabric detection, or seamless integration with smart home systems."*

# Designing AIDA: Manipulating Design Attributes

Method: System Design

## ■ Empathy

### **High Level:** Empathetic Check-in & Response

After user input, the system checks in with participants, for example, *“You did a great job! How do you feel following our conversation?”*.

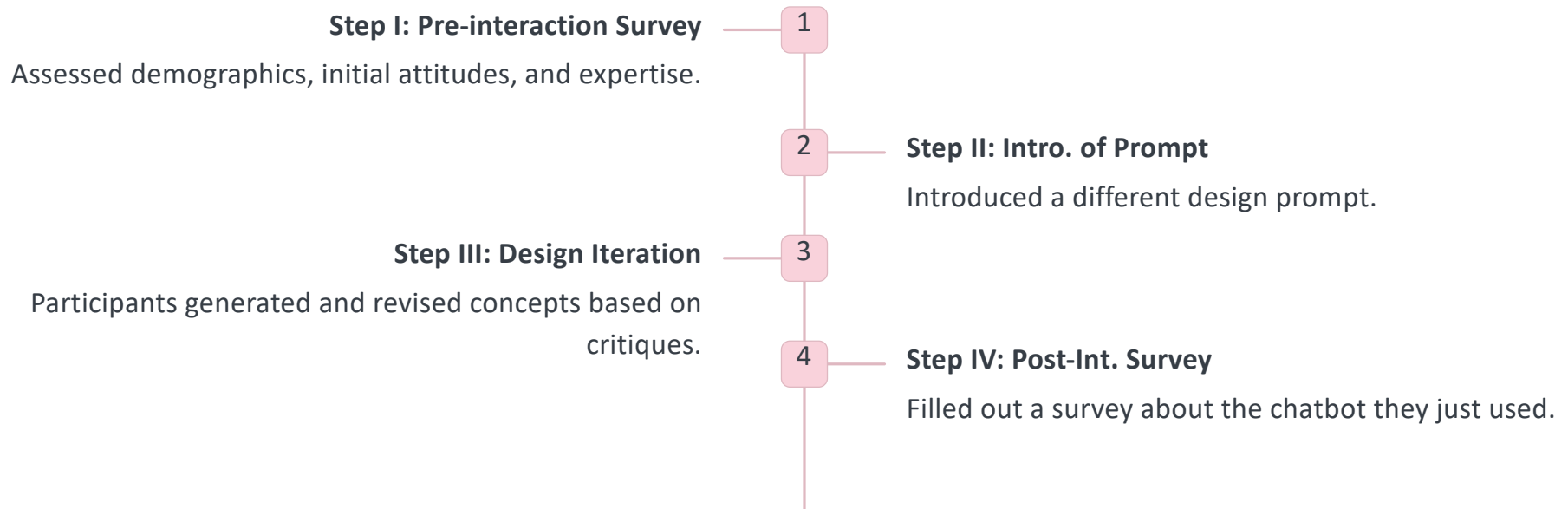
The empathetic chatbot acknowledges any emotional feedback using a first-person tone, such as *“I am glad that you are enjoying the session”*.

### **Low Level:** Non-empathetic Acknowledgment

- A non-empathetic chatbot, representing a low level of empathetic behavior, merely acknowledges receiving the responses

# A Four-step Process, Looped for Four Design Versions

## Experimental Procedure



# Participant Demographics & Initial Attitude

## Results

### ■ Participants' Demographics

- 56 valid participants were recruited via Prolific and compensated with 12 USD for an average study duration of 61.06 minutes.
- A mix of ages and genders, with over 80% having obtained a college degree or higher. None reported professional experience as a product or mechanical designer.

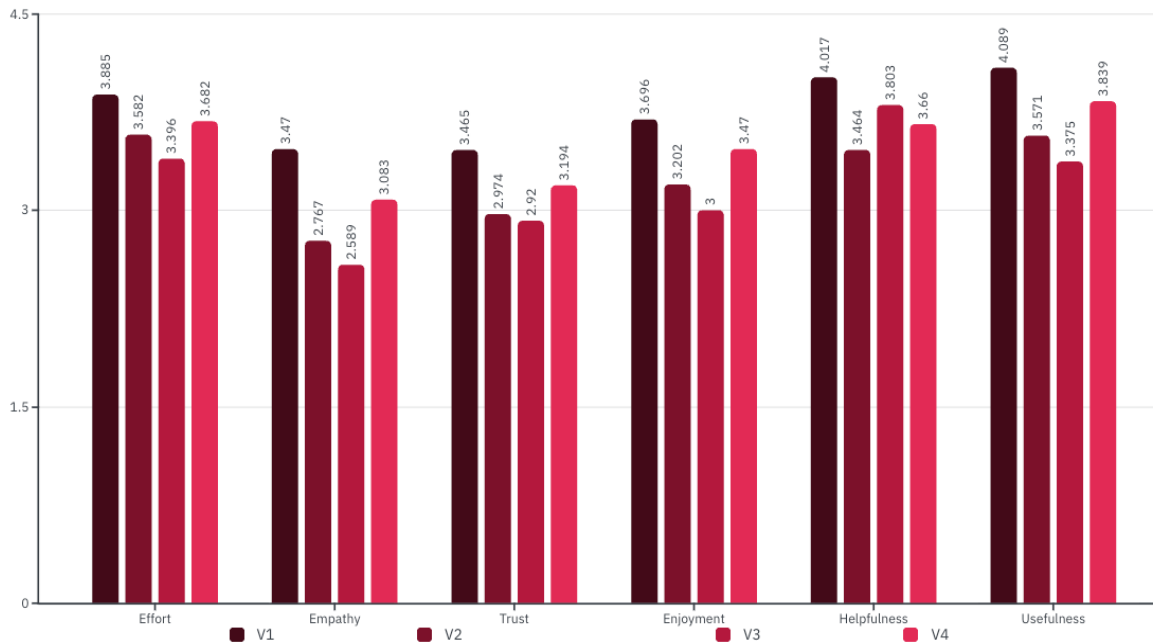
### ■ Initial Attitudes:

- Participants reported a high level of familiarity and knowledge of chatbots on average before the interaction began.

Metric	Mean	SD
Initial Trust	3.435	0.684
Anthropomorphism	1.999	1.163
Bot Experience	4.053	0.719
Bot knowledge	4.214	0.574

# Post-interaction Attitudes For Each Version

## Results



- AIDA chatbot V1 (human avatar, detailed explanation, empathetic behavior) resulted in the highest level of self-reported trust, perceived effort, enjoyment, and usefulness.
- V4 (abstract icon, general feedback, empathetic behavior) scored second-highest in trust, effort, enjoyment, and usefulness.

# Trust and Usefulness Differ Across Design Versions

## Results & Analysis

- Self-reported attitudes were compared across the four chatbot versions using ANOVA.
- The results show significant group differences in several key attitudes:
  - Perceived Effort ( $p = 0.023$ )
  - **Trust ( $p < 0.001$ )**
  - Enjoyment ( $p = 0.014$ )
  - Usefulness ( $p = 0.002$ )



# Deeper Dive: Which Factors Predict Trust?

## Results & Analysis

- A linear mixed model was used to account for variables of interest as fixed effects and variability across subjects as random effects, allowing for the analysis of data with repeated measures.

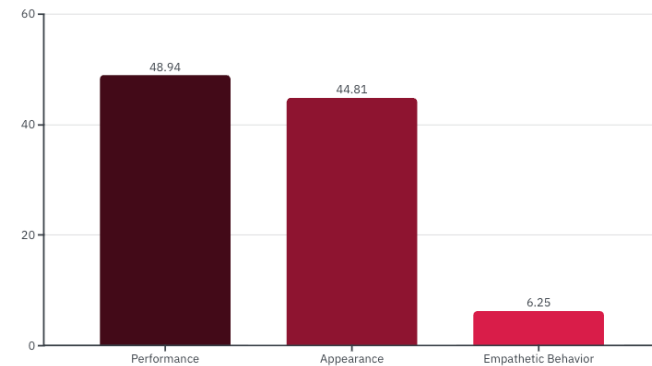
- **Empathetic Behavior** had a significant and positive effect ( $p < 0.001$ ).
- A participant's **Initial Trust** was a significant and positive predictor ( $p < 0.05$ ).
- **Age** acted as a significant factor ( $p < 0.05$ ), where trust decreased as age increased.
- **Performance** had a marginally significant effect ( $p < 0.1$ ) in enhancing trust.

VARIABLE	COEF.	T-VAL	P-VAL
Appearance	0.056	1.199	0.230
Performance	0.081	1.738	0.082
Empathetic Behavior	0.190	4.059	0.000
Initial Trust	0.176	2.433	0.014
Gender	-0.227	-0.918	0.407
Age	-0.011	-2.478	0.013

# Deeper Dive: What is the Relative Importance of Each Attribute?

## Results & Analysis

- Conjoint analysis was conducted to find the attribute part-worth.
- The analysis confirmed that a high level of each attribute leads to higher perceived trust.
- When forced to make trade-offs, users placed the most importance on **Performance (48.94%)** and **Appearance (44.81%)**.
- **Empathetic Behavior** was found to have the smallest importance (6.25%) on user-reported trust.



Relative importance of design attributes

# Resolving the Discrepancy

## Discussion: Reconciling the Analytical Methods

- There was a discrepancy between the two analytical methods: while empathetic behavior was found to be statistically significant in the regression model, conjoint analysis showed it had a relatively low importance.
- This can be attributed to their different objectives.
  - Linear Regression evaluates statistical association.
  - Conjoint analysis estimates the relative importance of attributes in participants' choices.

### Reliability

Empathy is a statistically **reliable** way to boost trust.

### Relative Weight

Performance and Appearance are the most **influential** factors in driving a user's overall **preference** for one system over another.

# Compensatory Power of Empathy

## Discussion

### ■ A Standout Finding:

- The chatbot with empathetic behavior, even with an abstract icon and non-detailed feedback, led to higher perceived effort, enjoyment, and usefulness compared to the other two non-empathetic versions.

### ■ Implication:



Providing empathetic responses or building emotional connections with users may **compensate for the poor performance** of interactive systems.

- Acknowledging users' emotions requires a certain system layer, and this effort is well recognized.

# Limitations & Future Work

## ■ **Limitations:**

- This study only considered three system design attributes and only two levels for each.
- The study was conducted online and was not fully controlled; participants spent approximately an hour on average.

## ■ **Future Work:**

- This paper presents preliminary data analysis; interaction effectiveness and design outcomes will be examined from the interaction transcript in the next stage.
- Sentiment analysis will be conducted to track the emotional trend and look for creativity-enhancing sentiments.
- Future exploration of a more granular scale for design attributes will be practically helpful.

# Conclusions

Empirical results support the hypothesis that high-level design attributes foster greater trust in AI-assisted design ideation.

System performance and empathetic behavior have a significant impact on trust, while individual differences like initial trust and age also play a critical role.

Trust is built based on both individual trust propensity and interactions with a certain trustee.

Empathetic design can meaningfully enhance user experience and may serve as a compensatory mechanism when other system attributes are suboptimal.

Integrating statistical modeling with preference-based analysis provides complementary insights to guide future design decisions.



# THANK YOU

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