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The role of cognitive engagement propensity and mind perception in trust in artificial intelligence among young adults

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Abstract

Trust in artificial intelligence (AI) is crucial for effective human–AI collaboration, particularly in decision-making contexts. While prior research has emphasized system characteristics such as transparency and reliability, limited attention has been given to underlying psychological processes. The present study examined the role of Cognitive Engagement Propensity (CEP), along with Agency and Experience Attribution, in predicting Trust in AI within an integrated theoretical framework. Grounded in dual-process theory, mind perception theory, and models of automation trust, a quantitative cross-sectional design was employed among young adult AI users. The findings revealed that CEP was positively associated with Trust in AI, as well as with both Agency and Experience Attribution. Controlling for demographic variables, CEP emerged as a significant predictor of trust. Agency Attribution uniquely predicted Trust in AI, whereas Experience Attribution did not contribute additional explanatory value. Age and gender were not significant predictors of trust, although gender differences were observed in cognitive engagement and attribution patterns. Overall, the results suggest that trust in AI is primarily influenced by cognitive evaluations of competence rather than demographic factors or affective impressions.

Keywords: Trust in AI; Cognitive Engagement Propensity; Agency Attribution; Experience Attribution; Mind Perception; Young Adults

1. Introduction

Artificial intelligence (AI) has rapidly evolved from a specialized computational tool into an integral part of everyday decision-making across domains such as healthcare, finance, education, and transportation. Modern AI systems are designed to perform tasks that typically require human intelligence, including learning, reasoning, pattern recognition, and adaptive decision-making (Russell & Norvig, 2021). However, the effectiveness of these systems is not determined solely by their technical accuracy but also by users' willingness to trust and rely on them.

Trust in AI is fundamentally a psychological construct that reflects an individual's willingness to accept vulnerability based on positive expectations regarding a system's competence, reliability, and consistency (Glikson & Woolley, 2020). Given that many AI systems operate through complex and opaque processes, users often evaluate their outputs without fully understanding how decisions are generated. Therefore, identifying the psychological factors that influence trust is essential for improving human–AI interaction and ensuring appropriate reliance.

Research on trust in automation suggests that trust plays a central role in determining reliance behavior (Lee & See, 2004). Both under-trust and over-trust can lead to suboptimal outcomes, particularly in high-stakes environments. Trust is dynamic and evolves over time as users interact with systems and update their mental models based on feedback (Hoff & Bashir, 2015). While prior research has primarily focused on system-level characteristics such as

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transparency and reliability, comparatively less attention has been given to individual differences and cognitive attribution processes.

1.1. Cognitive Engagement Propensity

Cognitive Engagement Propensity, often conceptualized as Need for Cognition, refers to an individual's tendency to engage in and enjoy effortful cognitive activities (Cacioppo & Petty, 1982). Individuals high in cognitive engagement are more likely to process information systematically and analytically rather than relying on intuitive judgments. According to dual-process theories (Evans & Stanovich, 2013; Kahneman, 2011), such individuals are more likely to evaluate AI systems critically, paying attention to cues related to competence and reasoning processes. This suggests that cognitive engagement may play a significant role in shaping trust in AI.

1.2. Mind Perception: Agency and Experience Attribution

Mind perception theory proposes that individuals attribute mental capacities to entities along two primary dimensions: agency and experience (Gray et al., 2007). Agency refers to the perceived ability to act intentionally, plan, and make decisions, whereas experience refers to the capacity to feel emotions and subjective states. AI systems are generally perceived as high in agency but low in experience. These attributions can influence how users evaluate AI systems. Agency attribution may enhance perceptions of competence and reliability, thereby increasing trust, while experience attribution may contribute to anthropomorphic perceptions and perceived relatability.

1.3. Demographic Influences on Trust in AI

Demographic factors such as age and gender may also influence trust in AI systems. Age can affect familiarity with technology and openness to adopting new systems, while gender differences have been observed in cognitive engagement and technology-related confidence (Cacioppo et al., 1996; Venkatesh & Morris, 2000). However, findings in this area remain inconsistent, highlighting the need for further investigation within integrated models.

1.4. Aim and Objectives of the Study

1.4.1. Aim

The aim of the present study is to examine how Cognitive Engagement Propensity, Agency Attribution, Experience Attribution, Age, and Gender relate to and predict Trust in Artificial Intelligence.

1.4.2. Objectives

- To examine the relationships among Cognitive Engagement Propensity, Agency Attribution, Experience Attribution, and Trust in Artificial Intelligence.
- To determine whether Agency Attribution and Experience Attribution significantly predict Trust in Artificial Intelligence.
- To assess whether Age and Gender significantly predict Trust in Artificial Intelligence.
- To evaluate whether Cognitive Engagement Propensity, Agency Attribution, and Experience Attribution significantly predict Trust in Artificial Intelligence after controlling for Age and Gender.
- To examine gender differences in Cognitive Engagement Propensity, Agency Attribution, and Trust in Artificial Intelligence.
- To compare Trust in Artificial Intelligence between participants scoring high and low on Cognitive Engagement Propensity

1.5. Hypotheses

- $H_0$1: There is no significant relationship between Cognitive Engagement Propensity (CEP) and Trust in Artificial Intelligence.
- $H_0$2: There is no significant relationship between Cognitive Engagement Propensity (CEP) and Agency Attribution.
- $H_0$3: There is no significant difference between males and females in Cognitive Engagement Propensity.
- $H_0$4: There is no significant difference between males and females in Agency Attribution.
- $H_0$5: There is no significant difference in Trust in Artificial Intelligence between participants scoring high and low on Cognitive Engagement Propensity.
- $H_0$6: Age does not significantly predict Trust in Artificial Intelligence.
- $H_0$7: Gender does not significantly predict Trust in Artificial Intelligence.

- $H_0$8: Cognitive Engagement Propensity does not significantly predict Trust in Artificial Intelligence after controlling for Age and Gender.
- $H_0$9: Agency Attribution does not significantly predict Trust in Artificial Intelligence after controlling for Age, Gender, and Cognitive Engagement Propensity.
- $H_0$10: Experience Attribution does not significantly predict Trust in Artificial Intelligence after controlling for Age, Gender, and Cognitive Engagement Propensity

1.6. Significance of the Study

This study contributes to both theoretical and practical understanding of trust in artificial intelligence. Theoretically, it advances existing literature by examining how Cognitive Engagement Propensity, Agency Attribution, and Experience Attribution, along with demographic variables, jointly influence trust in AI, thereby addressing a gap in integrated models of human–AI interaction.

Practically, the findings can inform the design and implementation of AI systems by identifying key cognitive and perceptual factors that shape user trust. This can assist developers and organizations in improving user training, system design, and decision-making processes, ultimately enhancing appropriate reliance, user engagement, and overall interaction with AI systems.

2. Materials and Methods

2.1. Research Design

A quantitative, cross-sectional correlational design was used to examine relationships among Cognitive Engagement Propensity (CEP), Agency Attribution, Experience Attribution, and Trust in Artificial Intelligence. Regression and comparative analyses were conducted to assess predictive relationships and group differences.

2.2. Participants

The sample consisted of 230 participants (122 males, 108 females) aged 18–37 years ($M = 21.70$, $SD = 2.92$). Participants were required to be at least 18 years old, proficient in English, and regular users of AI tools. Individuals with cognitive or attention-related difficulties were excluded. No missing data were observed for key variables.

2.3. Sampling Technique

Participants were recruited using convenience sampling. This approach was appropriate for accessing individuals with regular AI usage and ensured adequate sample size for statistical analyses.

2.4. Measures

- **Need for Cognition Scale (NCS-6)** CEP was measured using the six-item NCS-6 (Coelho et al., 2020) on a 7-point Likert scale. Higher scores indicate greater cognitive engagement ($\alpha \approx .87$).
- **Short Trust in Automation Scale (S-TIAS)** Trust in AI was assessed using the S-TIAS (McGrath et al., 2025), rated on a 7-point Likert scale ($\alpha \approx .82$).
- **Mind Perception Scale** Agency and Experience Attribution were measured using subscales of the Mind Perception Scale (Gray et al., 2007), assessing perceived intentionality and emotional capacity.

2.5. Data Analysis

Data were analyzed using Jamovi (Version 2.7.14). Descriptive statistics (mean, standard deviation, skewness, kurtosis) were computed to assess distributional properties.

Pearson correlation was used to examine relationships among variables. Hierarchical regression analysis assessed predictors of Trust in AI while controlling for Age and Gender. Independent samples t-tests examined gender differences and differences in Trust in AI between high and low CEP groups (median split). Statistical significance was set at .05.

3. Results and Discussion

The study examined relationships among Cognitive Engagement Propensity (CEP), Agency Attribution, Experience Attribution, Age, Gender, and Trust in Artificial Intelligence using Jamovi (Version 2.7.14). Results are presented through descriptive statistics, correlations, t-tests, and regression.

Table 1 Descriptive Statistics for Study Variables (N = 230)

Variable	M	SD	Minimum	Maximum	Skewness	Kurtosis
CEP	19.00	3.52	6	30	0.15	1.63
Experience	28.40	14.20	0	63	-0.36	-0.58
Agency	42.50	14.80	0	77	-0.63	0.42
Trust in AI	48.90	9.67	12	84	0.10	2.43
Age	22.60	4.85	18	51	3.02	11.70

Table 1 presents descriptive statistics for Cognitive Engagement Propensity (CEP), Experience Attribution, Agency Attribution, Trust in AI, and Age.

CEP (M = 19.00, SD = 3.52), Experience (M = 28.40, SD = 14.20), Agency (M = 42.50, SD = 14.80), and Trust in AI (M = 48.90, SD = 9.67) showed acceptable skewness and kurtosis values, indicating approximately normal distributions suitable for parametric analysis.

Age (M = 22.60, SD = 4.85) showed high positive skewness and kurtosis, indicating non-normality. However, it was retained due to the robustness of parametric tests in large samples (N = 230). Overall, the data met assumptions for further statistical analyses.

Table 2 Correlations Among CEP, Trust in AI, and Agency

Variable	1	2	3
CEP	—		
Trust in AI	0.430***	—	
3. Agency	0.275***	0.402***	—

Note. N=230. Pearson's *r* values are reported. p < .05, ** p < .01, *** p < .001.

Table 2 presents Pearson correlations among CEP, Trust in AI, and Agency Attribution (N = 230).

$H_0$1: There is no significant relationship between Cognitive Engagement Propensity (CEP) and Trust in AI.

A moderate positive correlation was found, $r(228) = .430$, $p < .001$, indicating that higher cognitive engagement is associated with greater trust in AI. This aligns with trust in automation models, which suggest that analytical evaluation supports calibrated trust (Lee & See, 2004).

$H_0$2: There is no significant relationship between Cognitive Engagement Propensity (CEP) and Agency Attribution.

A significant positive correlation was observed, $r(228) = .275$, $p < .001$, suggesting that individuals with higher cognitive engagement are more likely to attribute agency to AI, consistent with dual-process perspectives emphasizing systematic processing.

Additional finding suggests that Trust in AI was positively correlated with Agency Attribution, $r(228) = .402$, $p < .001$, indicating that perceiving AI as autonomous and goal-directed is associated with higher trust, in line with mind perception theory (Gray et al., 2007).

Table 3 Gender Differences in CEP

Variables	Male[a]		Female[b]		t (228)	p	Cohen's d
	M	SD	M	SD			
CEP	19.60	3.76	18.30	3.11	2.85	0.005	0.38

Note. N = 230. M = mean; SD = standard deviation. [a] n = 122. [b] n = 108. p < .05. p < .01. *** p < .001.

Table 3 presents gender differences in Cognitive Engagement Propensity (CEP).

$H_0$3: There is no significant difference between males and females in Cognitive Engagement Propensity (CEP).

A significant difference was observed, t(228) = 2.85, p = .005, d = .38. Males (M = 19.60, SD = 3.76) reported higher CEP than females (M = 18.30, SD = 3.11), indicating a small-to-moderate effect.

This finding may be understood through social role theory, which suggests that gender differences in cognitive styles can reflect cultural expectations (Eagly & Wood, 2012). It is also consistent with research showing variation in analytical engagement across genders in STEM-related contexts (Cheryan et al., 2017).

Table 4 Gender Differences in Agency

Variables	Male[a]		Female[b]		t (228)	p	Cohen's d
	M	SD	M	SD			
Agency	45.40	14.38	39.30	14.73	3.15	0.002	0.42

Note. N = 230. M = mean; SD = standard deviation. [a] n = 122. [b] n = 108. p < .05. p < .01.

*** p < .001.

Table 4 presents gender differences in Agency Attribution.

$H_0$4: There is no significant difference between males and females in Agency Attribution. A significant difference was found, t(228) = 3.15, p = .002, d = .42. Males (M = 45.40, SD = 14.38) reported higher agency attribution than females (M = 39.30, SD = 14.73), indicating a moderate effect.

This finding aligns with mind perception theory, which identifies agency as a key dimension in attributing mental capacities (Gray et al., 2007). Prior research also suggests that perceptions of non-human agents, including AI, can vary across individuals, including gender differences (Waytz et al., 2010; Eyssel et al., 2012).

Table 5 Gender Differences in Experience

Variables	Male[a]		Female[b]		t (228)	p	Cohen's d
	M	SD	M	SD			
Experience	30.50	13.56	26.10	14.56	2.37	0.019	0.31

Note. N = 230. M = mean; SD = standard deviation. [a] n = 122. [b] n = 108. p < .05. p < .01. *** p < .001.

Table 5 presents gender differences in Experience Attribution.

There is no significant difference between males and females in Experience Attribution.

A significant difference was found, t(228) = 2.37, p = .019, d = .31. Males (M = 30.50, SD = 13.56) reported higher experience attribution than females (M = 26.10, SD = 14.56), indicating a small-to-moderate effect.

Experience attribution represents the second dimension of mind perception (Gray et al., 2007). Although prior research often reports higher empathic tendencies among females (Christov-Moore et al., 2014), the present findings suggest variation in how emotional capacities are attributed to AI across genders.

Table 6 Differences in Trust in AI Between Low and High CEP Groups

Variables	Low CEP[a]	High CEP[b]		t (228) p	Cohen's d		
	M	SD	M	SD			
Trust in AI	46.60	8.55	52.60	10.30	−4.79	< 0.001	0.66

Note. N = 230. M = mean; SD = standard deviation. [a] n = 142. [b] n = 88. Mean difference = −6.01. SE difference = 1.25.

Table 6 presents differences in Trust in AI between low and high CEP groups.

H_05: There is no significant difference in Trust in AI between participants scoring high and low on Cognitive Engagement Propensity.

A significant difference was observed, $t(228) = −4.79$, $p < .001$, $d = .66$. Participants with high CEP ($M = 52.60$, $SD = 10.30$) reported greater trust than those with low CEP ($M = 46.60$, $SD = 8.55$), indicating a medium-to-large effect.

This suggests that higher cognitive engagement is associated with greater trust in AI, consistent with models emphasizing perceived ability and usefulness as key determinants of trust and technology acceptance (Mayer et al., 1995; Davis, 1989).

Table 7 Hierarchical Regression Results Predicting Trust in AI

Variable	*B*	*95%CI*		*SE*	*β*	*R*²	Δ*R*²
		LL	UL				
Step 1						0.003	0.003
Intercept	48.405***	42.320	54.440	3.063			
Age	−0.002	-0.265	0.261	0.133	−0.001		
Gender[a]	1.110	-1.438	3.659	1.293	0.115		
Step 2						0.189	0.185***
Intercept	28.870***	21.224	36.516	3.880			
Age	−0.123	-0.363	0.117	0.122	−0.062		
Gender[a]	−0.317	-2.654	2.021	1.186	−0.033		
CEP	1.214***	0.881	1.547	0.169	0.442		
Step 3						0.289	0.100***
Intercept	25.676***	18.332	33.020	3.727			
Age	−0.173	-0.339	0.0543	0.115	−0.087		
Gender[a]	−1.264	-3.489	0.9610	1.129	−0.131		
CEP	0.999***	0.6767	1.3212	0.164	0.364		
Experience	0.080	0.0332	0.1921	0.057	0.117		
Agency	0.156**	0.0465	0.2656	0.056	0.239		

Note. $N = 230$; *p < .05. **p < .01. ***p < .001.

Table 7 presents the hierarchical regression analysis predicting Trust in AI.

H_06: Age does not significantly predict Trust in AI.

H_07: Gender does not significantly predict Trust in AI.

In Step 1, age ($B = -0.002$, $p = .986$) and gender ($B = 1.110$, $p = .392$) were not significant predictors, explaining only 0.3% of the variance ($R^2 = .003$). This suggests that demographic variables alone do not meaningfully influence trust, consistent with the Technology Acceptance Model, which emphasizes cognitive evaluations over demographics (Davis, 1989).

$H_0$8: Cognitive Engagement Propensity does not significantly predict Trust in AI after controlling for Age and Gender.

The addition of CEP significantly improved the model ($\Delta R^2 = .185$, $p < .001$). CEP emerged as a strong positive predictor ($B = 1.214$, $\beta = .442$, $p < .001$), indicating that higher cognitive engagement is associated with greater trust. This aligns with trust models highlighting perceived competence as central to trust formation (Mayer et al., 1995).

$H_0$9: Agency Attribution does not significantly predict Trust in AI after controlling for Age, Gender, and Cognitive Engagement Propensity.

In the final model, Agency was a significant predictor ($B = 0.156$, $\beta = .239$, $p = .005$), suggesting that perceiving AI as autonomous and goal-directed increases trust. This supports attribution theory, which links perceived intentionality to judgments of reliability (Heider, 1958).

$H_0$10: Experience Attribution does not significantly predict Trust in AI after controlling for Age, Gender, and Cognitive Engagement Propensity.

Experience was not a significant predictor ($B = 0.080$, $p = .166$), indicating that emotional attributions to AI contribute less to trust compared to competence and agency.

Overall, the final model explained 28.9% of the variance in Trust in AI ($R^2 = .289$), highlighting the stronger role of cognitive and perceptual factors over demographic variables.

4. Summary and Conclusion

This study examined whether trust in AI is influenced more by demographic factors such as age and gender or by psychological processes such as Cognitive Engagement Propensity and mind perception including agency and experience. Drawing on theories of trust in automation, mind perception, and technology acceptance, trust was conceptualized as a cognitive and perceptual process.

4.1. Summary of Findings

Trust in AI was positively associated with Cognitive Engagement Propensity, Agency Attribution, and Experience Attribution at the correlational level. Individuals who engaged in deeper analytical thinking and those who perceived AI as intentional and goal directed reported higher trust.

Gender differences were observed in Cognitive Engagement Propensity, Agency Attribution, and Experience Attribution, with males scoring higher, but no significant gender differences were found in trust.

Regression results showed that age and gender contributed minimally to trust. Cognitive Engagement Propensity emerged as the strongest predictor, followed by Agency Attribution, while Experience Attribution did not uniquely predict trust. Overall, trust was primarily driven by cognitive and perceptual factors rather than demographic variables.

5. Conclusion

The findings indicate that trust in AI is shaped more by psychological processes than demographic characteristics. Individuals who engage in analytical thinking and perceive AI as capable and autonomous are more likely to trust it. Trust develops through cognitive evaluation of competence and agency rather than emotional or demographic influences.

5.1. Implications

5.1.1. Theoretical Implications

The results support models of trust in automation by highlighting the role of cognitive evaluation. Cognitive Engagement Propensity emerged as a key factor, indicating that effortful thinking influences trust formation. Within mind perception theory, agency but not experience uniquely predicted trust, suggesting that perceived competence is more important than emotional attribution.

5.2. Practical Implications

Improving trust in AI should focus on enhancing transparency, clarity, and user engagement rather than targeting demographic groups. Designing systems that clearly communicate how they function and make decisions may strengthen perceptions of competence and agency, thereby increasing trust.

5.3. Limitations

The cross sectional design limits causal interpretation. The sample may restrict generalizability across different populations and contexts. Although the model explained 28.9 percent of the variance, other factors such as risk perception, prior experience, and transparency were not included. The high correlation between agency and experience also suggests possible overlap.

5.4. Recommendations for Future Research

Future studies should use longitudinal or experimental designs to examine causal relationships. Including additional variables such as perceived risk, transparency, and prior experience with AI could improve explanatory power. Advanced methods such as structural equation modeling and research across diverse contexts may further clarify the psychological basis of trust in AI.

Compliance with ethical standards

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Disclosure of conflict of interest

The author declares that there are no financial or non-financial conflicts of interest related to this study.

Statement of ethical approval

The study was conducted in accordance with ethical guidelines for research involving human participants.

Statement of informed consent

Informed consent was obtained from all participants prior to data collection. Participation was voluntary and confidentiality of responses was maintained.

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