ARCHETYPE
Jurnal Ilmiah Psikologi & Terapan

# PSYCHOLOGICAL PREDICTORS OF USER TRUST IN ARTIFICIAL INTELLIGENCE: EVIDENCE FROM SECONDARY DATA ANALYSIS

**Putu Dhanu Driya[1], Ni Putu Abigail Firsta Sumerta[2], Made Sunanda Ayu Sandrina[3]**
[1] Information System Study Program, Faculty of Engineering and Vocational, Universitas Pendidikan Ganesha
[2] Program Studi Magister Sains Psikologi, Faculty of Psychology, Soegijapranata Catholic University
[3] English Education Study Program, Faculty of Languages and Arts, Universitas Pendidikan Ganesha

[1]dhanu.driya@undiksha.ac.id

**Article Information** | **ABSTRAK**

**Received:**
12 Desember 2025

**Revised:**
18 Mei 2026

**Published:**
29 April 2026

**ABSTRACT**

User trust in artificial intelligence (AI) is shaped by a complex interaction of cognitive and experiential factors, yet empirical evidence regarding how these psychological determinants jointly predict trust remains limited. This study examines psychological predictors of user trust in AI using secondary data obtained from a publicly available Kaggle dataset involving 6,678 participants. Five psychological predictors cognitive load, trust history, prior AI exposure, time pressure, and cultural factors were analyzed using correlational and multiple regression techniques. The findings indicate that trust history was the strongest positive predictor of user trust ($\beta = .485$, $p < .001$), whereas cognitive load significantly reduced trust ($\beta = –.151$, $p < .001$). Other predictors did not demonstrate statistically significant independent effects within the present model. The regression model explained 25.7% of the variance in trust scores, indicating moderate explanatory power within the analyzed dataset. These findings suggest that cognitive ease and positive prior experiences with AI may play an important role in shaping user trust. However, the findings should be interpreted cautiously due to the use of secondary cross-sectional data and broad variable operationalization. This study contributes to Human AI Interaction research by clarifying the relative contribution of selected psychological predictors of AI trust and by offering practical implications for the design of more reliable and user-friendly AI systems.

**Keywords:** Artificial Intelligence, Cognitive Load, Human AI Interaction, Psychological Determinants, Trust History, User Trust, UX Research

## Introduction

Artificial intelligence (AI) has become deeply embedded in everyday digital interactions, Artificial intelligence (AI) has become increasingly integrated into everyday digital activities, influencing how individuals search for information, make decisions, access services, and complete tasks (Pham et al., 2024). As AI systems are more widely implemented in areas such as healthcare, finance, education, customer service, and digital platforms, user trust has emerged as a critical factor shaping the effectiveness of Human AI Interaction (Bach et al., 2024). Trust determines whether users accept AI recommendations, rely on automated decisions, or continue using AI-supported systems (Glikson & Woolley, 2020). Without sufficient trust, the effectiveness and adoption of AI technologies may be significantly reduced (McGrath et al., 2025). Consequently, understanding the factors that influence user trust has become an important concern in AI, Human–Computer Interaction (HCI), and UX research.

Recent studies suggest that trust in AI is influenced not only by system-level characteristics such as accuracy, transparency, or explainability, but also by psychological and experiential factors brought by users into the interaction process (De Freitas et al., 2023). Contemporary literature identifies several psychological determinants associated with trust formation, including cognitive load, prior experience, trust history, time pressure, and cultural orientation (Afroogh et al., 2024; Yang et al., 2025). Cognitive Load Theory suggests that systems requiring excessive mental effort may reduce perceived usability and confidence (Sweller et al., 2011), whereas experiential trust theories emphasize that repeated positive interactions strengthen users' expectations regarding system reliability (Mayer et al., 1995). Previous research has also shown that situational and contextual conditions may shape how users evaluate AI systems and determine whether they feel comfortable relying on algorithmic recommendations (Marmolejo Ramos et al., 2024).

Despite growing interest in psychological determinants of AI trust, existing empirical findings remain fragmented. Many previous studies focus on isolated variables, such as cognitive load alone or prior experience independently, without comparing the relative contribution of multiple psychological predictors within a single analytical framework (Merritt et al., 2015; Zhou et al., 2019). In addition, several studies emphasize technological determinants of trust while paying comparatively less attention to human-side psychological mechanisms. This creates a theoretical and empirical gap regarding which psychological factors most strongly contribute to trust formation in AI systems.

To address this gap, the present study examines psychological predictors of user trust in AI using secondary data from a publicly available Kaggle dataset. Specifically, the study investigates the contribution of cognitive load, trust history, prior AI exposure, time pressure, and cultural factors in predicting user trust in AI. Using correlational and multiple regression analyses, this study aims to identify which psychological variables demonstrate the strongest relationship with trust within the analyzed dataset.

This study contributes to Human AI Interaction research by integrating multiple psychological predictors into a single analytical framework and comparing their relative predictive influence on user trust in AI. The findings are expected to provide practical insight for researchers, designers, and developers in creating AI systems that are more cognitively accessible, reliable, and user-centered.

## Research Methods

This study employed a quantitative cross-sectional design using secondary data obtained from the publicly available Human AI Interaction dataset published on Kaggle by Ehtesham Malik (Malik, 2025). The dataset contains data related to user interaction with AI systems, including trust calibration, cognitive evaluation, AI familiarity, and behavioral responses during interaction with artificial intelligence technologies. The original data were compiled from user-based AI interaction studies involving recommender systems, conversational agents, and decision-support tools.

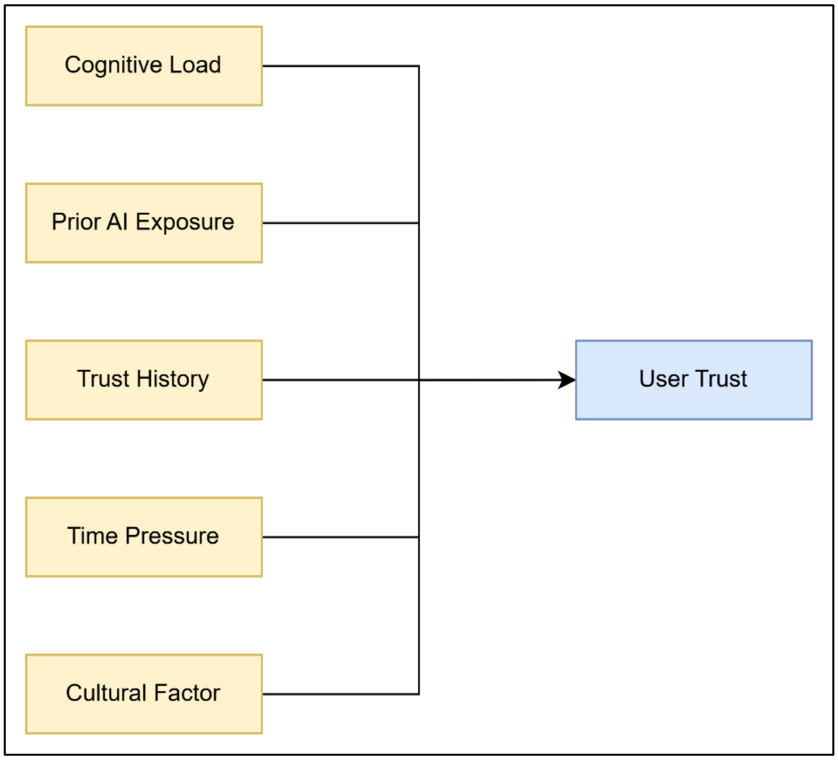


Figure 1. Variables in The Research

The study focused on examining psychological predictors of user trust in AI, specifically cognitive_load, trust_history, prior_ai_exposure, time_pressure, and cultural_factor, with latent_trust_score serving as the dependent variable. The dataset consisted of 6,678 valid observations obtained from participants with diverse demographic and technological backgrounds. Inclusion criteria were limited to cases containing complete information for all predictor variables and the dependent variable. Cases with incomplete records, duplicated entries, inconsistent coding structures, or missing values in core variables were excluded during the preprocessing stage to ensure analytical consistency and reliability.

Data cleaning procedures were conducted prior to statistical analysis. The cleaning process included checking for duplicate cases, variable harmonization, consistency verification, and screening for outliers and incomplete observations. Missing-value treatment was performed using listwise deletion because the proportion of missing data in the selected variables was relatively low and incomplete cases could potentially bias regression estimation. To improve comparability across measures originating from different source studies, several continuous variables, including cognitive_load, trust_history, and time_pressure, were normalized into a standardized 0–1 range.

Meanwhile, prior_ai_exposure and cultural_factor were retained as ordinal coded variables ranging from 1 to 3 based on the original dataset categorization.

The operationalization of variables was based on the conceptual definitions provided in the dataset documentation and associated metadata. Cognitive load referred to the perceived mental effort experienced during AI interaction and was primarily represented through task-difficulty indicators and cognitive workload measures. Trust history represented users' prior positive experiences with AI or automated systems. Prior AI exposure reflected users' familiarity and frequency of interaction with AI technologies. Time pressure represented perceived urgency or temporal constraints during interaction tasks, while cultural factor referred to broad demographic or cross-national categorizations available within the dataset. The dependent variable, latent_trust_score, represented a composite trust indicator derived from trust ratings, reliance measures, and AI acceptance evaluations contained in the original data source.

The research instruments consisted of psychometric scales, trust questionnaires, cognitive workload indicators, and behavioral interaction measures used in the original studies contributing to the dataset. Although the instruments were not directly administered by the researchers, the operational definitions and measurement consistency of the variables were carefully evaluated to maintain conceptual alignment across observations.

Statistical analysis was conducted in several stages using descriptive and inferential techniques. Descriptive statistics were first employed to examine data distributions, central tendencies, and variability. Pearson correlation analysis was then conducted to identify relationships among variables. Multiple linear regression analysis served as the primary analytical method for examining the predictive contribution of psychological factors toward user trust in AI. Multicollinearity diagnostics were evaluated using Variance Inflation Factor (VIF) and tolerance values to ensure the adequacy of the regression model. Model fit was assessed using $R^2$, adjusted $R^2$, and regression significance testing. To maintain methodological consistency with the reported analyses, unsupported moderation and interaction-effect claims were removed from the revised manuscript.

## Results and Discussion

### Results

The study analyzed data from 6,678 respondents. Descriptive statistics for all variables are presented in Table 1.

**Table 1. Descriptive Statistics**

| Variable | N | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|
| cognitive_load | 6678 | 0.0001 | 0.9998 | 0.496294 | 0.2865632 |
| trust_history | 6678 | 0.0002 | 0.9998 | 0.495147 | 0.2885635 |
| prior_ai_exposure | 6678 | 1 | 3 | 1.79 | 0.750 |
| time_pressure | 6678 | 0.0003 | 0.9997 | 0.500416 | 0.2889226 |
| cultural_factor | 6678 | 1 | 3 | 2.01 | 0.823 |
| latent_trust_score | 6678 | 38.3744 | 100.0000 | 70.368138 | 9.1150396 |

The variables cognitive load, trust history, and time pressure were distributed within a normalized 0–1 range. The variables prior ai exposure and cultural factor were coded within a 1–3 range. The dependent variable, latent trust score, had a mean score of 70.37 (SD = 9.12).

### Correlation Analysis

Pearson correlation analysis was conducted to examine relationships among the study variables. The results are presented in Table 2.

**Table 2. Correlations**

| Variable | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| 1. cognitive load | 1 | | | | | |
| 2. trust history | .003 | 1 | | | | |

| Variable | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| 3. prior ai exposure | .014 | .002 | 1 | | | |
| 4. time pressure | -.025* | .002 | .008 | 1 | | |
| 5. cultural factor | .028* | .002 | .008 | -.017 | 1 | |
| 6. latent trust score | -.149** | .484** | .009 | .013 | .006 | 1 |

*p < .05
**p < .01

The correlation analysis showed that trust history had a significant positive correlation with latent trust score ($r = .484$, $p < .001$). Cognitive load demonstrated a significant negative correlation with latent trust score ($r = –.149$, $p < .001$). The variables prior ai exposure ($r = .009$, $p = .456$), time pressure ($r = .013$, $p = .305$), and cultural factor ($r = .006$, $p = .638$) did not show statistically significant correlations with latent trust score.

Correlations among the independent variables were generally low ($r < .03$), indicating minimal association between predictors.

**Multiple Regression Analysis**

Multiple linear regression analysis was conducted to examine the predictive contribution of the psychological variables toward latent trust score. The regression coefficients are presented in Table 3.

**Table 3. Regression Coefficients**

| Predictor | B | Std. Error | Beta | t | Sig. |
|---|---|---|---|---|---|
| (Constant) | 64.611 | 0.444 | — | 145.426 | 0.000 |
| Cognitive load | -4.788 | 0.336 | -0.151 | -14.258 | 0.000 |
| Trust history | 15.315 | 0.333 | 0.485 | 45.958 | 0.000 |
| Prior ai exposure | 0.122 | 0.128 | 0.010 | 0.949 | 0.343 |

| Predictor | B | Std. Error | Beta | t | Sig. |
|---|---|---|---|---|---|
| Time pressure | 0.255 | 0.333 | 0.008 | 0.767 | 0.443 |
| Cultural factor | 0.102 | 0.117 | 0.009 | 0.869 | 0.385 |

Dependent Variable: latent trust score

The regression results indicated that trust history significantly predicted latent trust score ($\beta = .485$, $p < .001$). Cognitive load also demonstrated a statistically significant negative effect on latent trust score ($\beta = –.151$, $p < .001$).

The variables prior ai exposure ($p = .343$), time pressure ($p = .443$), and cultural factor ($p = .385$) did not demonstrate statistically significant effects in the regression model.

**Model Summary**

The regression model summary is presented in Table 4.

**Table 4. Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .507 | 0.257 | 0.257 | 7.8574332 |

The regression model produced an R value of .507 and an $R^2$ value of .257, indicating that the independent variables explained 25.7% of the variance in latent trust score. The adjusted $R^2$ remained stable at .257. The standard error of the estimate was 7.857.

## Discussion

The findings indicate that trust history emerged as the strongest predictor of user trust in AI. This result supports previous trust formation theories suggesting that repeated positive interactions contribute to stronger trust development over time (Mayer et al., 1995). Consistent with Human AI Interaction literature, prior successful experiences with automated systems may strengthen users' expectations regarding AI reliability and performance (Hancock et al., 2011). The strong contribution of trust history in the present study suggests that experiential familiarity plays an important role in shaping trust toward AI systems.

Cognitive load also demonstrated a significant negative relationship with user trust. This finding aligns with Cognitive Load Theory, which proposes that excessive mental effort may reduce user confidence and perceived usability (Sweller et al., 2011). Users may perceive AI systems requiring higher cognitive effort as more difficult, less intuitive, or less reliable. Similar findings have been reported in previous Human Computer Interaction research showing that cognitive strain may reduce trust and acceptance of automated systems (Yang et al., 2025).

In contrast, These variables did not demonstrate statistically significant independent effects within the present regression model. However, these findings should be interpreted cautiously because their influence may depend on contextual conditions, measurement precision, or moderating variables not included in the current analysis. However, these nonsignificant findings should be interpreted cautiously. The absence of significance does not necessarily indicate that these variables are unimportant in broader AI trust contexts. Their effects may depend on measurement precision, contextual conditions, domain-specific interactions, or moderating variables not examined in the current study. In particular, the cultural factor variable was operationalized using broad categorical coding, which may not adequately capture more nuanced cultural orientations relevant to AI trust formation.

The regression model explained 25.7% of the variance in user trust, indicating moderate explanatory power within the analyzed dataset. In behavioral and psychological research, trust is recognized as a complex construct influenced by multiple cognitive, social, technological, and contextual factors. Therefore, the current findings suggest that psychological variables, particularly trust history and cognitive load, contribute meaningfully to understanding user trust in AI, although additional factors outside the present model are also likely to influence trust formation.

Overall, the findings reinforce the importance of cognitive ease and positive user experience in Human AI Interaction. From a practical perspective, AI systems that are reliable, understandable, and cognitively accessible may contribute to stronger user trust over time. These findings also support the growing emphasis on user-centered and psychologically informed AI design approaches within UX and HCI research.

## Conclusion

This study sought to examine the psychological determinants of user trust in AI by testing a multi-factor model using large-scale secondary data. The results demonstrate that trust in AI is shaped primarily by two key psychological mechanisms: users' prior trust history with AI systems and their experienced cognitive load during interaction. Trust history emerged as the strongest predictor, indicating that consistent, positive past interactions build a foundation for trusting future AI technologies. Conversely, higher cognitive load significantly reduced trust, suggesting that when AI systems feel mentally taxing or difficult to use, users perceive them as less reliable and less worthy of confidence. These findings underscore the dual importance of cognitive ease and experiential familiarity in the formation of trust.

Other variables, including these variables did not demonstrate statistically significant independent effects within the present dataset and modeling framewor, did not contribute significantly to explaining trust when considered alongside the dominant predictors. This suggests that trust in AI is not meaningfully influenced by simple exposure, momentary situational constraints, or broad cultural categories, but rather by deeper psychological processes tied to user experience and mental effort. The regression model accounted for approximately 25.7% of the variance in user trust, demonstrating substantial explanatory power for psychological factors alone in a complex socio-technical phenomenon.

Overall, this study contributes to Human AI Interaction research by offering empirical evidence that user trust is systematically predictable through cognitive and experiential variables. For practitioners and designers, the findings highlight the importance of creating AI systems that reduce cognitive burden and deliver consistent, reliable interaction histories to reinforce trust over time. For researchers, the study offers direction for future inquiry, suggesting that nuanced emotional, contextual, and domain-specific moderators may further enrich our understanding of trust in AI. By emphasizing the centrality of cognitive load and experiential trust history, this research advances theoretical clarity and practical insight into how users come to rely on AI in their daily digital environments.

## References

Afroogh, S., Akbari, A., Malone, E., Kargar, M., & Alambeigi, H. (2024). Trust in AI: progress, challenges, and future directions. *Humanities and Social Sciences Communications*, *11*(1), 1–30. https://doi.org/10.1057/s41599-024-04044-8

Alasmari, A. A., Alruwaili, R. F., Alotaibi, R. F., Youssef, I. K., & Asklany, S. A. (2025). Demographic influences on trust in artificial intelligence across cognitive domains: A statistical perspective. *Plos One*, *20*(11 November). https://doi.org/10.1371/journal.pone.0331003

Bach, T. A., Khan, A., Hallock, H., Beltrão, G., & Sousa, S. (2024). A Systematic Literature Review of User Trust in AI-Enabled Systems: An HCI Perspective. *International Journal of Human-Computer Interaction*, *40*(5), 1251–1266. https://doi.org/10.1080/10447318.2022.2138826

Bellini-Leite, S. C. (2022). Dual Process Theory: Embodied and Predictive; Symbolic and Classical. *Frontiers in Psychology*, *13*(March), 1–11. https://doi.org/10.3389/fpsyg.2022.805386

David, K., Geihs, K., Leimeister, J. M., Roßnagel, A., Schmidt, L., Stumme, G., & Wacker, A. (2014). Socio-technical design of ubiquitous computing systems. *Socio-Technical Design of Ubiquitous Computing Systems*, 1–353. https://doi.org/10.1007/978-3-319-05044-7

De Freitas, J., Agarwal, S., Schmitt, B., & Haslam, N. (2023). Psychological Factors Underlying Attitudes Toward AI Tools. *Nature Human Behaviour*, *7*(11), 1845–1854. https://doi.org/10.1038/s41562-023-01734-2

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals*, *14*(2), 627–660. https://doi.org/10.5465/annals.2018.0057

Han, J., & Ko, D. (2025). Trust Formation, Error Impact, and Repair in Human–AI Financial Advisory: A Dynamic Behavioral Analysis. *Behavioral Sciences*, *15*(10), 1–25. https://doi.org/10.3390/bs15101370

Hancock, P. A., Billings, D. R., Schaefer, K. E., Chen, J. Y. C., De Visser, E. J., & Parasuraman, R. (2011). A meta-analysis of factors affecting trust in human-robot interaction. *Human Factors*, *53*(5), 517–527. https://doi.org/10.1177/0018720811417254

Islam, K. F., Awal, A., Mazumder, H., Munni, U. R., Majumder, K., Afroz, K., Tabassum, M. N., & Hossain, M. M. (2023). Social cognitive theory-based health promotion in primary care practice: A scoping review. *Heliyon*, *9*(4), e14889. https://doi.org/10.1016/j.heliyon.2023.e14889

Jiang, W., Li, D., & Liu, C. (2025). Understanding Dimensions of Trust in AI Through Quantitative Cognition: Implications for Human-AI Collaboration. *Plos One*, *20*(7 July), 1–17. https://doi.org/10.1371/journal.pone.0326558

Kroeger, F. (2019). Unlocking the treasure trove: How can Luhmann's theory of trust enrich trust research? *Journal of Trust Research*, *9*(1), 110–124. https://doi.org/10.1080/21515581.2018.1552592

Li, Y., Wu, B., Huang, Y., & Luan, S. (2024). Developing trustworthy artificial intelligence: insights from research on interpersonal, human-automation, and human-AI trust. *Frontiers in Psychology*, *15*(April), 1–13. https://doi.org/10.3389/fpsyg.2024.1382693

Malik, E. (2025). *Human-AI Interaction [Data set]*. Kaggle. https://doi.org/10.34740/kaggle/dsv/13207192

Marmolejo-Ramos, F., Marrone, R., Korolkiewicz, M., Gabriel, F., Siemens, G., Joksimovic, S., Yamada, Y., Mori, Y., Rahwan, T., Sahakyan, M., Sonna, B., Meirmanov, A., Bolatov, A., Som, B., Ndukaihe, I., Arinze, N. C., Kundrát, J., Skanderová, L., Ngo, V. G., … Tejada, J. (2024). Factors influencing trust in algorithmic decision-making: an indirect scenario-based experiment. *Frontiers in Artificial Intelligence*, *7*. https://doi.org/10.3389/frai.2024.1465605

Mayer, R. C., David, J. H., & Schoorman, F. D. (1995). An Integrative Model of ORganizational Trust. *Academy of Management Review*, *20*(3), 709–734. https://doi.org/10.3390/g13030039

McGrath, M. J., Lack, O., Tisch, J., & Duenser, A. (2025). Measuring Trust In Artificial Intelligence: Validation Of An Established Scale And Its Short Form. *Frontiers in Artificial Intelligence*, *8*(May). https://doi.org/10.3389/frai.2025.1582880

Mehrotra, S., Degachi, C., Vereschak, O., Jonker, C. M., & Tielman, M. L. (2024). A Systematic Review on Fostering Appropriate Trust in Human-AI Interaction: Trends, Opportunities and Challenges. *ACM Journal on Responsible Computing*, *1*(4), 1–45.

https://doi.org/10.1145/3696449

Merritt, S. M., Lee, D., Unnerstall, J. L., & Huber, K. (2015). Are Well-Calibrated Users Effective Users? Associations Between Calibration of Trust and Performance on an Automation-Aided Task. *Human Factors*, *57*(1), 34–47. https://doi.org/10.1177/0018720814561675

Mylrea, M., & Robinson, N. (2023). Artificial Intelligence (AI) Trust Framework and Maturity Model: Applying an Entropy Lens to Improve Security, Privacy, and Ethical AI. *Entropy*, *25*(10). https://doi.org/10.3390/e25101429

Nugraha, I., & Fatwanto, A. (2021). User Experience Design Practices in Industry (Case Study from Indonesian Information Technology Companies). *Elinvo (Electronics, Informatics, and Vocational Education)*, *6*(1), 49–60. https://doi.org/10.21831/elinvo.v6i1.40958

Paas, F., & van Merriënboer, J. J. G. (2020). Cognitive-Load Theory: Methods to Manage Working Memory Load in the Learning of Complex Tasks. *Current Directions in Psychological Science*, *29*(4), 394–398. https://doi.org/10.1177/0963721420922183

Pham, V. K., Pham Thi, T. D., & Duong, N. T. (2024). A Study on Information Search Behavior Using AI-Powered Engines: Evidence From Chatbots on Online Shopping Platforms. *SAGE Open*, *14*(4), 1–18. https://doi.org/10.1177/21582440241300007

Samson, K., & Kostyszyn, P. (2015). Effects of cognitive load on trusting behavior - An experiment using the trust game. *PLoS ONE*, *10*(5), 1–10. https://doi.org/10.1371/journal.pone.0127680

Sweller, J., Ayres, P., & Kalyuga, S. (2011). Cognitive Load Theroy. In *Intstructional Systems and PErformance Technologues* (Vol. 82, Issue 1).

Yang, R., Li, S., Qi, Y., Liu, J., He, Q., & Zhao, H. (2024). *Deciphering the Dynamics of Algorithm Trust: The Role of Task Objectivity, Time Pressure, and Cognitive Load*. SSRN Journal. https://ssrn.com/abstract=4931387

Yang, R., Li, S., Qi, Y., Liu, J., He, Q., & Zhao, H. (2025). Unveiling users' algorithm trust: The role of task objectivity, time pressure, and cognitive load. *Computers in Human Behavior Reports*, *18*(April), 100667. https://doi.org/10.1016/j.chbr.2025.100667

Zhou, J., Li, Z., Yu, K., Chen, F., Wang, Y., Hu, H., & Li, Z. (2019). Effects of influence on user trust in predictive decision making. *Conference on Human Factors in Computing Systems - Proceedings*, 23–39. https://doi.org/10.1145/3290607.3312962