Human Interaction and Emerging Technologies (IHIET 2025), Vol. 197, 2025, 411–421
https://doi.org/10.54941/ahfe1006734

Trusting the Machine – The Role of Gender and Personality in Shaping the Propensity to Trust Artificial Intelligence

Jona Stefan Karg, Janine Jäger, and Petra Maria Asprion

University of Applied Sciences and Arts Northwestern Switzerland FHNW, School of Business, Institute for Information Systems, Basel, Switzerland

ABSTRACT

With the growing significance of Digital Trust in the context of Artificial Intelligence (AI), it is essential to identify the factors that shape individuals' propensity to place trust in AI. This study examines whether gender differences exist in the propensity to trust AI and explores the extent to which personality traits serve as significant predictors of trust. Data from $N = 114$ students was collected using validated psychometric questionnaires. A one-way analysis of variance (ANOVA) was used to analyze gender differences, while a multiple linear regression analysis was used to examine the influence of personality traits. The results revealed no significant gender difference. However, the personality traits conscientiousness and neuroticism were significant negative predictors of the propensity to trust AI. Overall, the Big Five personality traits explained a moderate amount of the variance in the propensity to trust AI. The findings underscore the multifaceted nature of psychological factors influencing trust in AI and contribute to the expanding body of interdisciplinary research aimed at systematically understanding this complex phenomenon.

Keywords: Artificial intelligence, Human-AI interaction, Trust, Propensity to trust, Trustworthy AI

INTRODUCTION

The relevance of artificial intelligence (AI), which is increasingly used in data processing and interpretation, is growing in everyday life (Gebru et al., 2022). In this context, the importance of Digital Trust, defined as an individual's belief that organizations offering digital services and technology as well as the technology itself will safeguard the interests of all parties involved while preserving societal values, has emerged (Jäger et al., 2025). Concurrently, trust in AI is frequently discussed, given its substantial influence on both the development and use of AI (Hoffman et al., 2023). Trust is considered to be crucial to the acceptance and effectiveness of AI systems and therefore significantly influences their success (Gebru et al., 2022). In addition, trust is also regarded as a mediator for perceived AI system reliability. In general, trust can be understood as an attitude of a trustor towards a trustee, whereas trustworthiness describes different characteristics of the trustee itself which affect trust (Lewis & Marsh, 2022). In addition to an AI system's inherent trustworthiness (Lee & See, 2004), there are numerous interpersonal and intrapersonal aspects of the user that influence trust in AI (Gebru et al., 2022). Given its central role in human-AI interaction (Karg et al., 2025), there is a growing need for interdisciplinary research to understand the underlying factors that shape this propensity to trust generative, large-language-model-based (LLM) AI Systems.

Understanding of Trust

The relevance of the concept of trust has increased since the mid-1990s (Lee & See, 2004) due to the rise of self-organized teams and self-directed work, in which traditional management control mechanisms have been reduced or eliminated (Mayer et al., 1995). As a result, trust replaces the control function, since direct observation of employees is no longer possible. In addition, trust has proven to be a useful concept for describing human interaction with internet applications and automated systems (Lee & See, 2004). Mayer et al. (1995, p. 712) define trust as the willingness of trustors to make themselves vulnerable to the actions of a trustee. This is based on the expectation that the trustee will take a certain action that is relevant to the trustor, without them being able to control the trustee's behavior. Thus, trust can be understood as a willingness to take risks and accordingly, as an essential factor in risk perception.

On the one hand, trust is influenced by the trustworthiness of the trustee (Körber, 2019). In the field of technology, a definition was established in 2004 stipulating that systems that function efficiently and reliably are considered trustworthy (Lee & See, 2004). On the other hand, trust also differs from person to person, depending on personal characteristics; some people are more inclined to trust than others (Lee & See, 2004). In a technological context, individual differences – such as personality, cognitive traits or demographic factors – can significantly influence a person's propensity to place trust in a technical system (Lee & See, 2004). Therefore, it can be assumed that the propensity to trust varies depending on personality (Körber, 2019), whereby it is also considered a personality trait (Lee & See, 2004). Specifically, dependencies between the Big Five personality traits and trust have been observed (Hoff & Bashir, 2015). These personality traits, also known by the acronym OCEAN include openness, conscientiousness, extraversion, agreeableness, and neuroticism (Kovbasiuk et al., 2024). They are representing a broad dimension of human personality that influence how individuals perceive and interact with their environment, including technology.

Trust and AI

As AI becomes more relevant in daily life as well as for private and enterprises' decision making, trust research in this respect is also gaining importance (Bedué & Fritzsche, 2022). For example, Gebru et al. (2022) highlight trust as a fundamental factor in the successful implementation of technology. Shin (2021) explains that trust in AI is rooted in the assumption that AI systems work in a trustworthy way and thus reflect their reliability and credibility. Accordingly, organizations developing or offering AI systems should ensure and prove the accuracy of AI system outputs. Schepman and Rodway (2023) consider the ability of the AI system to perform a task reliably to be the primary foundation of trust. In addition to this perceived task performance, transparent and dependable processes, as well as the clear purpose of the AI system to help users achieve a better performance, are essential components of perceived trustworthiness (Solberg et al., 2022).

Besides the trustworthiness of an AI system – also referred to as the trustee – individual characteristics of users – the trustors – and therefore their attitude towards AI, also play a significant role in shaping trust in AI (Sindermann et al., 2022). These characteristics include numerous interpersonal and intrapersonal factors, which are referred to as dispositional trust (Solberg et al., 2022) or general trust (Schepman & Rodway, 2023). They are considered crucial for understanding both the acceptance of and trust in AI systems (Sindermann et al., 2022) and are collectively defined as propensity to trust AI (Montag et al., 2023). Research shows that the propensity to trust AI has a direct influence on the level of trust users place in AI technologies (Solberg et al., 2022).

In conclusion, the propensity to trust is user-specific, trustworthiness is system-specific, and Digital Trust is both context-specific and relational. Accordingly, Digital Trust arises from the dynamic interaction between the user's propensity to trust and their perception of the system's trustworthiness within a specific usage context. Understanding individual trust propensities helps to predict Digital Trust outcomes, like willingness to adopt AI, data sharing in general, or acceptance of automation.

Gender and AI

Among other factors gender has been proven to influence trust in AI in a meta-analysis (Kaplan et al., 2023), with men demonstrating greater trust in AI than women. However, those findings are not consistent across the literature and have been contradicted by another study (Montag et al., 2023). Hoff and Bashir (2015) point out that gender differences have an impact on human interaction with different technologies and Solberg et al. (2022) go one step further and assign a decisive role to gender in propensity to trust, referring to Hoff and Bashir (2015). In contrast, Razin and Feigh (2023) emphasize the inconsistency of findings across studies, indicating that the influence of gender on trust in AI remains unclear. Given these opposing results, it is essential to further explore the role of gender in trust formation, as this could contribute to the development of more human-centered AI systems.

Personality Traits and AI

In addition to the role of gender in AI systems trustworthiness, the Big Five personality traits offer further insights into how people interact with AI systems (Kovbasiuk et al., 2024). For example, the Big Five personality trait openness refers to a person's curiosity and willingness to engage in new experiences, including interactions with new technologies such as generative, LLM-based AI. Individuals high in conscientiousness are characterized as responsible and organized; this can suggest a preference for dependable and reliable AI systems. The trait extraversion describes the outgoing social nature of an individual, potentially favoring engaging AI systems. Agreeableness is the trait that is most closely related to trust and refers to the willingness to cooperate; individuals high on this trait might prefer AI systems that encourage teamwork and collaboration. Finally, neuroticism is the propensity to be exposed to negative emotions; therefore, it might be associated with higher concern when it comes to AI. These personality traits are considered to be significant predictors of trust in the context of AI (Kaplan et al., 2023), however, similar to the findings on the impact of gender those findings vary greatly.

For instance, Schepman and Rodway (2023) state that the influence of personality on the attitude towards AI can vary depending on the specific technology and the measuring instrument. According to Kaplan et al. (2023), people with a higher degree of openness tend to trust an AI system more. In contrast, Sindermann et al. (2022) found this correlation regarding the attitude towards AI only in their Chinese, but not in their German sample. This suggests that the propensity to trust AI could also be influenced by culture (Solberg et al., 2022). Furthermore, Schepman and Rodway (2023) observed a correlation with conscientiousness, but only towards a negative attitude regarding AI. The same studies also report a correlation with extraversion, while Kaplan et al. (2023) does not. However, both studies indicate that extroverted people are more likely to trust AI systems. Besides, Schepman and Rodway (2023) have also observed a positive correlation with agreeableness, but once again only towards a negative attitude regarding AI. In addition, neuroticism also shows a negative correlation with trust (Kaplan et al., 2023). In some cases it is even the only Big Five personality trait to influence the propensity to trust AI (Sindermann et al., 2022). However, the theoretical and empirical findings are contradictory, not only in the context of different cultures. Given these inconsistencies, further research into the role of personality traits is essential to better understand individual differences in trust in AI and to support the development of more adaptive and trustworthy systems.

METHOD

This study examines whether (H_1) the propensity to trust AI differs based on gender and (H_2) the Big Five personality traits (a) openness, (b) conscientiousness, (c) extraversion, (d) agreeableness, and (e) neuroticism are influencing the propensity to trust AI. The data for both analyses is based on the same ad hoc sample, which was drawn during lectures of a bachelor's program in Business Information Technology at a Swiss University. This sample was selected for convenience and was considered sufficient for this exploratory study, even if this excludes generalizability. Data was collected via an anonymous online survey. At the beginning of the survey, the purpose of the data collection and investigation was briefly explained, followed by additional information about the voluntary nature, and the data processing, which had to be actively consented to.

The cross-sectional study comprises a data set of $N = 114$ subjects. One subject was removed from the sample because all items were answered with the mid-scale value of 3. In addition, four subjects were excluded because several items of individual subscales remained unanswered. For subjects with only one missing value in a subscale, this was replaced using the median. Two subjects stated that they had no experience with generative, LLM-based AI systems, and another two did not provide an answer for this item. These four subjects were excluded from the analysis. Thus, a lack of experience with AI was defined as a hard exclusion criterion, since otherwise the quality of the data in relation to the measured trust in technology would have to be questioned (Siegrist, 2021). Hence, $N = 105$ subjects were considered for this study. Among the sample were $n = 54$ men and $n = 51$ women. In addition, $n = 12$ subjects did not provide their age; the remaining $n = 93$ subjects were on average $M = 22.09$ years old ($SD = 3.98$) at the time of the survey.

In line with Hoffman et al. (2023), the Trust in Automation Questionnaire (TiA) by Körber (2019) – developed according to classical test theory – was used to measure the propensity to trust AI. For this purpose, the three items of the propensity to trust subscale ($\omega = .78$) were adapted to the context of AI systems by replacing the word "automated" with "AI". Due to the reliability of this questionnaire and the small sample size, a factor analysis and measurement of internal consistency was not carried out (Bujang et al., 2018). Age was measured with natural numbers to achieve the metric level of measurement. Data analysis was performed using R (R Core Team, 2022). Prior to the data analysis, negative items were reversed. Subsequently, the mean values of the individual interval-scaled items of the respective scales were calculated as new variables, except for the single item variable age. The effect size was evaluated in accordance with the conventions of Cohen (1992) and the significance level was set at $p = .05$.

Analysis of Gender Differences

The sample for analyzing gender differences included all $N = 105$ subjects, so no further data sets were removed. The a priori power analysis using G*Power (Faul et al., 2007) showed that a sample size of $N = 159$ for three groups respectively $N = 128$ for two groups is required for a significant medium effect ($f > 0.25$, $p = 0.05$, $1\text{-}\beta = 0.80$) according to Cohen (1992). Therefore, the sample size of $N = 105$ does not provide sufficient statistical power.

Gender was measured nominally in a single item based on the three options "female", "male", and "diverse", with the latter not being selected by any of the subjects. The analysis of the gender difference was carried out using a one-way analysis of variance (ANOVA) without repeated measures. Therefore, the prerequisite of normal distribution was tested initially using the Shapiro-Wilk test ($p = .010$), which indicated a violation of this assumption. The data was visually inspected using a histogram and a QQ plot, which also indicated a violation of the prerequisite. In addition, the D'Agostino significance test ($p = .016$) revealed a skewed distribution. Although ANOVA is considered to be relatively robust to violations of the normal distribution assumption, distortions of results are possible (Schmider et al., 2010). Therefore, the ordinal scaled Kruskal-Wallis test was used in addition to the ANOVA to compare the two results and to ensure that the violation of the prerequisite had no influence on the results.

Analysis of Personality Traits

For the multiple linear regression analysis of correlations between personality traits and the propensity to trust AI, outliers were diagnosed using Cook's distance of the r-package olsrr (Hebbali, 2024). This analysis identified eight outliers, which were consequently excluded from the analysis. This resulted in a sub-sample of $n = 97$. An a priori power analysis was carried out (Faul et al., 2007), which indicated that for a significant medium effect ($f^2 > .15$, $p = .05$, $1\text{-}\beta = .80$) according to Cohen (1992), a sample size of $N = 55$ is required.

The Big Five personality traits were measured using the German-language NEO-Five-Factor-Inventory-30 (NEO-FFI-30) developed by Körner et al. (2008), an economical German-language version of the NEO-FFI, which was translated from English by Borkenau and Ostendorf (1993, cited in Körner et al., 2008). The five subscales with six items each relate to the robust personality factors according to Costa and McCrae (1989, cited in Körner et al., 2008), including openness ($\alpha = .67$), conscientiousness ($\alpha = .78$), extraversion ($\alpha = .72$), agreeableness ($\alpha = .75$), and neuroticism ($\alpha = .81$). For reasons of economy, only half of the items, based on the factor loadings reported by Körner et al. (2008), were selected. Consequently, only 15 items were used instead of the actual 30 items of the NEO-FFI-30 (Körner et al., 2008). This was done to avoid a longer survey time, a high dropout rate, and hence a loss of quality (Galesic & Bosnjak, 2009). For the same reasons as mentioned in the context of the TiA (Körber, 2019), no factor analysis and measurement of internal consistency were conducted. To examine the influence of personality on the propensity to trust AI, a multiple regression analysis was carried out. Since a causal relationship can be assumed in the context of the hypotheses and the underlying theory, a regression analysis was preferred over a correlation analysis. Prior to the analysis, the prerequisite assumptions were tested and did not indicate any violation.

RESULTS

Gender Differences

The descriptive analysis of the means, standard deviations and medians of the propensity to trust AI already indicated that there are no significant gender differences, with the different measures being almost identical (see Table 1). Accordingly, no significant gender difference ($F_{(1,103)} = .602$, $p = .440$, $1\text{-}\beta = .057$) could be identified by the ANOVA. This result was also reflected in the Kruskal-Wallis test ($\chi^2 = .629$, $p = .428$, $1\text{-}\beta = .080$).

Table 1: Descriptive measures of propensity to trust AI by gender *(N = 105)*.

	N	$M_{\text{Propensity}}$	$SD_{\text{Propensity}}$	$Md_{\text{Propensity}}$
Female	51	2.82	.67	2.67
Male	54	2.92	.68	2.67

Personality Traits

The multiple linear regression analysis revealed a significant relation between the personality factors and the propensity to trust AI ($F_{(5,91)} = 3.26$, $R^2 = .152$, $R^2{}_{adj} = .105$, $p = .009$, $1\text{-}\beta = .993$), with the five factors explaining 15.2 % of the variance in the propensity to trust AI. However, only conscientiousness ($\beta = -.255, p = .017$) and neuroticism ($\beta = -\ .291$, $p = .005$) are significantly negatively regressing with propensity to trust AI. The correlations of openness ($\beta = .167$, $p = .104$), extraversion ($\beta = .041, p = .696$), and agreeableness ($\beta = .142, p = .198$) are positive but not significantly correlating with propensity to trust AI. The results of the multiple regression analysis are shown in Table 2.

Table 2: Multiple regression analysis for personality traits on propensity to trust AI (n = 97).

	B	β	p
Constant	3.526		
Openness	.109	.167	.104
Conscientiousness	–.230*	–.255*	.017
Extraversion	.033	.041	.696
Agreeableness	.114	.142	.198
Neuroticism	–.215*	–.291*	.005
R^2	.152*	.009	

DISCUSSION

This study investigates whether gender differences and personality traits are significant predictors of the propensity to trust AI. The results of the ANOVA revealed no significant gender differences. However, this cannot be linked to the lack of test power, since the Kruskal-Wallis test confirms this result given the desired power. Hence, this result contradicts the assumption from Kaplan et al. (2023) and hypothesis 1, that the propensity to trust AI differs based on gender. Consequently, the results reflect the findings of Montag, et al. (2023). According to this study, gender does not seem to have an influence on the propensity to trust AI, indicating that gender may not be a universal predictor of AI trust. However, it raises the question of the effects shown in earlier studies (Kaplan et al., 2023) and whether those are rather based on the technical affinity of the users than gender. Therefore, the results call for further research on gender differences but also technical affinity, especially since the broader population is increasingly confronted with AI in their everyday life (Gebru et al., 2022). Research and design strategies should avoid overgeneralizing gender-based assumptions and instead consider more nuanced, context-specific factors such as culture.

Regarding personality traits, conscientiousness and neuroticism were small significant negative predictors of the propensity to trust AI. However, the positive regressions with openness, extraversion and agreeableness were not significant, whereby the analysis could be considered to be overpowered. Overall, the Big Five personality traits significantly explained a moderate percentage of the variance in the propensity to trust AI. Hence, the assumption from hypothesis 2, that personality traits influence the propensity to trust AI is supported. Interestingly, the authors are only aware of one other study (Schepman & Rodway, 2023), that also found a relationship with conscientiousness. In addition, the correlation with neuroticism highlighted by Kaplan et al. (2023) was also identified.

Personality-based differences offer valuable insight into how people evaluate and respond to AI systems. Although the Big Five factors conscientiousness, extraversion and agreeableness are conceptually linked to how individuals perceive specific characteristics of AI systems (Kovbasiuk et al., 2024) and the propensity to trust AI is not system-specific (Solberg et al., 2022) conscientiousness showed a significant relationship with the propensity to trust in this study. This negative correlation with conscientiousness appears plausible, because conscientious individuals value reliability and dependability, traits that may not always be evident in current AI systems. Reliability and dependability are often generalized across AI systems, yet many current AI systems may not be perceived as meeting these expectations. Therefore, it is not only essential to develop AI systems that are genuinely reliable and dependable, but also to effectively communicate these qualities to users at the point of deployment. In addition, system designers could consider offering more transparent explanations, control options, or reliability cues.

In contrast, it is remarkable that openness, which is associated with the willingness to experience new technologies such as AI, did not significantly correlate with the propensity to trust. An explanation might be the homogeneity of the sample regarding age, technology affinity and academic background, for which a general openness towards new technologies can be assumed. However, this homogeneity does not contradict the fact that the results show a significant negative association of neuroticism with the propensity to trust AI. On the contrary, it calls for transparent communication of the functionality of the respective AI system to counteract negative emotions towards AI.

Limitations

Since the sample can be considered homogeneous, consisting exclusively of students of the same technology focused program with a narrow age deviation, the results cannot be generalized and might have impacted the lack of gender differences. In contrast, the meta analytic gender differences reported by Kaplan et al. (2023) may have been partially influenced by associated stereotypes in relation to technology affinity. This raises the question of whether gender may only have a mediating role in the propensity to trust AI, relevant in more diverse populations but less so in this study. While there might be concerns about sample size and statistical power, the Kruskal-Wallis test results suggest these factors were likely not critical limitations in this sample.

In addition to the technology affinity homogeneity of the sample, the heterogeneity of cultural background and age must also be questioned. Even though Switzerland can be considered culturally heterogeneous and students from neighboring countries and with a migration background could also be part of the sample, this demographic data was not collected. Even though this study contains the data necessary to analyze correlations between age and the propensity to trust, the authors decided not to do so since only a minor age deviation was expected in this sample, which the descriptive analysis confirms.

Finally, the fact that the correlation of propensity to trust AI and openness according to Kaplan et al. (2023) and in the Chinese sample of Sindermann et al. (2022) was not confirmed in this study could be explained by the operationalization of this personality trait. In particular, the measurement of openness using the German-language NEO-FFI-30 is controversial since this scale has a relatively low communality and low internal consistencies (Körner et al., 2008). Future studies could benefit from English-language or domain-specific measures of openness to better assess its role in shaping trust in AI.

CONCLUSION

This study contributes to the important research on trust in AI by examining the influence of gender and personality traits on individuals' propensity to trust AI systems. Contrary to some previous findings, no significant gender differences were observed, suggesting that gender may not be a universal predictor of trust in AI. In contrast, personality traits, particularly conscientiousness and neuroticism, were identified as significant predictors, with both showing negative correlations with the propensity to trust AI. These findings support the perspective that trust in AI is not only determined by the technical characteristics of a system and therefore its trustworthiness but is also shaped by individual differences. Openness, extraversion, and agreeableness, while positively correlated, did not significantly predict trust, indicating that their influence may be more context-dependent or subtle. Designing AI systems that are perceived as trustworthy requires not only transparent and reliable system behavior but also sensitivity to the diversity of users' personalities and trust predispositions. Additionally, gender and personality are just two out of many relevant factors considered to influence the propensity to trust AI. Therefore, future research should investigate other factors such as age, technology affinity and previous experience. Thereby, human-AI interactions should continuously be explored – ideally across cultural contexts – to enable the development of more inclusive and human-centered AI systems and thus promote overall Digital Trust. This could ensure that AI systems are not only technically trustworthy but are also perceived as such by users.

ACKNOWLEDGMENT

This paper is based on the results of a master's thesis research and the study did not receive any funding. The master's thesis was supervised by Prof. Dr. Frank Ritz and Prof. Dr. Yanik Sterchi in cooperation with Prof. Dr. Oliver Bendel and the Digital Trust Competence Center (digitaltrust-competence.ch).

REFERENCES

Bedué, P., & Fritzsche, A. (2022). Can we trust AI? An empirical investigation of trust requirements and guide to successful AI adoption. *Journal of Enterprise Information Management*, *35*(2).

Bujang, M. A., Omar, E. D., & Baharum, N. A. (2018). A Review on Sample Size Determination for Cronbach's Alpha Test: A Simple Guide for Researchers. *Malaysian Journal of Medical Sciences*, *25*(6).

Cohen, J. (1992). A power primer. *Psychological Bulletin*, *112*(1).

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*(2).

Galesic, M., & Bosnjak, M. (2009). Effects of Questionnaire Length on Participation and Indicators of Response Quality in a Web Survey. *Public Opinion Quarterly*, *73*(2).

Gebru, B., Zeleke, L., Blankson, D., Nabil, M., Nateghi, S., Homaifar, A., & Tunstel, E. (2022). A Review on Human–Machine Trust Evaluation: Human-Centric and Machine-Centric Perspectives. *IEEE Transactions on Human-Machine Systems*, *52*(5).

Hebbali, A. (2024). *olsrr: Tools for Building OLS Regression Models*.

Hoff, K. A., & Bashir, M. (2015). Trust in Automation: Integrating Empirical Evidence on Factors That Influence Trust. *Human Factors*, *57*(3).

Hoffman, R. R., Mueller, S. T., Klein, G., & Litman, J. (2023). Measures for explainable AI: Explanation goodness, user satisfaction, mental models, curiosity, trust, and human-AI performance. *Frontiers in Computer Science*, *5*.

Jäger, J., Karg, J., Asprion, P. M., & Misyura, I. (2025). The Digital Trust Radar – A structured collection and analysis of global AI guidelines. In T. Ahram, A. Lopez Arquillos, J. Gandarias, & A. Morales Casas (Eds.), *AHFE (2025) International Conference* (Vol. 161). AHFE International.

Kaplan, A. D., Kessler, T. T., Brill, J. C., & Hancock, P. A. (2023). Trust in Artificial Intelligence: Meta-Analytic Findings. *Human Factors*, *65*(2).

Karg, J. S., Ritz, F., & Asprion, P. M. (2025). Propensity Matters – An Empirical Analysis on the Importance of Trust for the Intention to Use Artificial Intelligence. *Submitted at Human Interaction and Emerging Technologies (IHIET 2025)* (ahead-of-print).

Körber, M. (2019). Theoretical Considerations and Development of a Questionnaire to Measure Trust in Automation. In S. Bagnara, R. Tartaglia, S. Albolino, T. Alexander, & Y. Fujita (Eds.), *Proceedings of the 20th Congress of the International Ergonomics Association (IEA 2018)*. Springer International Publishing.

Körner, A., Geyer, M., Roth, M., Drapeau, M., Schmutzer, G., Albani, C., Schumann, S., & Brähler, E. (2008). Persönlichkeitsdiagnostik mit dem NEO-Fünf-Faktoren-Inventar: Die 30-Item-Kurzversion (NEO-FFI-30). *PPmP - Psychotherapie · Psychosomatik · Medizinische Psychologie*, *58*(6).

Kovbasiuk, A., Triantoro, T., Przegalińska, A., Sowa, K., Ciechanowski, L., & Gloor, P. (2024). The personality profile of early generative AI adopters: A big five perspective. *Central European Management Journal* (ahead-of-print).

Lee, J. D., & See, K. A. (2004). Trust in Automation: Designing for Appropriate Reliance. *Human Factors*, *46*(1).

Lewis, P. R., & Marsh, S. (2022). What is it like to trust a rock? A functionalist perspective on trust and trustworthiness in artificial intelligence. *Cognitive Systems Research*, *72*.

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An Integrative Model of Organizational Trust. *The Academy of Management Review*, *20*(3).

Montag, C., Kraus, J., Baumann, M., & Rozgonjuk, D. (2023). The propensity to trust in (automated) technology mediates the links between technology self-efficacy and fear and acceptance of artificial intelligence. *Computers in Human Behavior Reports*, *11*.

R Core Team. (2022). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna. https://www.r-project.org/

Razin, Y. S., & Feigh, K. M. (2023). *Converging Measures and an Emergent Model: A Meta-Analysis of Human-Automation Trust Questionnaires*.

Schepman, A., & Rodway, P. (2023). The General Attitudes towards Artificial Intelligence Scale (GAAIS): Confirmatory Validation and Associations with Personality, Corporate Distrust, and General Trust. *International Journal of Human–Computer Interaction*, *39*(13).

Schmider, E., Ziegler, M., Danay, E., Beyer, L., & Bühner, M. (2010). Is it really robust? *Methodology*, *6*(4).

Shin, D. (2021). The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. *International Journal of Human-Computer Studies*, *146*.

Siegrist, M. (2021). Trust and Risk Perception: A Critical Review of the Literature. *Risk Analysis*, *41*(3).

Sindermann, C., Yang, H., Elhai, J. D., Yang, S., Quan, L., Li, M., & Montag, C. (2022). Acceptance and Fear of Artificial Intelligence: Associations with personality in a German and a Chinese sample. *Discover Psychology*, *2*(1), 8.

Solberg, E., Kaarstad, M., Eitrheim, M. H. R., Bisio, R., Reegård, K., & Bloch, M. (2022). A Conceptual Model of Trust, Perceived Risk, and Reliance on AI Decision Aids. *Group & Organization Management*, *47*(2).