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Factors Influencing Public Trust in AI Decision Support Systems: A Cognitive and Behavioral Perspective

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ABSTRACT: Public trust represents a critical prerequisite for the responsible adoption of artificial intelligence based decision support systems (AI DSS), particularly in high stakes contexts where algorithmic recommendations may substantially influence consequential human decisions. Despite increasing reliance on AI DSS, the cognitive and behavioral mechanisms underlying public trust remain insufficiently understood, particularly regarding how transparency interacts with individual resistance to algorithmic decision making. This study examined the cognitive and behavioral determinants of trust in AI DSS using a cross sectional survey of 412 adults. Perceived transparency, algorithm aversion, anthropomorphism, need for cognition, general attitudes toward AI, perceived risk, and prior AI experience were examined as potential determinants of trust. Hierarchical multiple regression and moderation analyses were conducted to identify significant predictors and conditional relationships, while analysis of variance was used to assess differences in trust according to prior AI experience. The cognitive and behavioral factors collectively explained approximately 50% of the variance in trust. Perceived transparency emerged as the strongest positive predictor, followed by favorable attitudes toward AI, whereas perceived risk and algorithm aversion significantly reduced trust. Importantly, algorithm aversion significantly moderated the relationship between transparency and trust, such that the positive effect of transparency weakened as algorithm aversion increased. Trust also differed significantly according to prior AI experience, with highly experienced participants reporting greater trust than those with limited experience. These findings demonstrate that transparency, although important, is insufficient as a standalone mechanism for establishing trust in AI DSS. The study advances understanding of AI trust by demonstrating that the effectiveness of transparency depends partly on users' preexisting cognitive and behavioral dispositions toward algorithmic systems. Consequently, responsible trust building strategies should integrate understandable and context appropriate explanations, effective risk communication, meaningful user experience, and explicit consideration of individual differences in attitudes toward algorithmic decision making.

KEYWORDS: Artificial intelligence; decision support systems; public trust; algorithm aversion; perceived transparency

1. Introduction

Artificial intelligence based decision support systems (AI DSS) are increasingly deployed to assist or augment human judgment across high stakes domains, including healthcare diagnostics, financial lending, human resource screening, and public administration [1]. As algorithmic recommendations become more deeply embedded in consequential decision making, their effectiveness depends not only on technical accuracy but also on whether users are willing to accept and appropriately rely on their outputs. Public trust has therefore emerged as a critical determinant of the adoption, sustained use, and societal value of AI DSS [2]. Insufficient trust may lead users to disregard accurate and beneficial recommendations, whereas excessive or poorly calibrated trust may encourage inappropriate reliance on erroneous outputs. Understanding the cognitive and behavioral mechanisms that shape trust is therefore essential for achieving appropriate human reliance on AI supported decision making.

Trust in automation has traditionally been conceptualized as a dynamic psychological state that influences an individual's willingness to rely on a system under conditions characterized by uncertainty and vulnerability. This trust develops through interactions among characteristics of the human trustor, attributes of the automated system, and the context in which human system interaction occurs [1]. Building on this perspective, meta analytic evidence has demonstrated that trust in AI is associated with multiple dispositional factors, including propensity to trust and prior experience; perceived system characteristics, including reliability, transparency, and anthropomorphism; and situational factors, including task risk and workload [3–5]. Trust should therefore not be understood as a single or static attitude. Rather, it reflects a multidimensional psychological evaluation arising from interacting cognitive appraisals, prior experiences, perceptions of system characteristics, and behavioral tendencies.

One particularly important behavioral phenomenon within this literature is algorithm aversion, which describes the tendency of individuals to lose confidence in and abandon algorithmic recommendations more readily than comparable human advice after observing an algorithm make an error, even when the algorithm remains objectively more accurate [6]. This phenomenon presents an important challenge for AI DSS because even highly accurate systems may fail to achieve effective adoption when users react disproportionately to visible algorithmic errors. Subsequent research has demonstrated that algorithm aversion can be reduced when users are provided with even limited control over algorithmic outputs, indicating that aversion is malleable rather than an immutable disposition [7]. A systematic review of algorithm aversion research further categorized its antecedents according to users' expectations and expertise, their need for decision autonomy, and the broader cognitive and incentive structures surrounding the decision task [8]. These findings suggest that algorithm aversion represents a complex cognitive and behavioral response to the design, framing, and perceived autonomy of AI supported decision making rather than a simple rejection of automation.

Transparency represents another central determinant of trust in AI DSS. Providing users with information regarding how an algorithm generates recommendations is generally expected to increase understanding and facilitate appropriate reliance. However, empirical evidence has demonstrated that transparency does not invariably strengthen trust. Behavioral experiments have shown that greater transparency may sometimes reduce trust when explanations increase the cognitive burden associated with interpreting algorithmic reasoning without producing a corresponding increase in perceived system competence [9]. Evidence incorporating

physiological measures of cognitive load has similarly indicated that the effectiveness of visualized AI explanations depends partly on the compatibility between explanation format and users' cognitive processing capacity [10]. Earlier human factors research also demonstrated that presenting dynamic and real time confidence information could facilitate better calibrated trust and more appropriate reliance on decision aids [11]. Collectively, these findings indicate that transparency should not be treated as a universally effective mechanism for increasing trust. Its influence may depend on individual cognitive characteristics and preexisting attitudes toward algorithmic decision making.

The importance of these psychological mechanisms becomes particularly apparent in high consequence applied environments. A systematic review examining trust in AI based clinical decision support systems among healthcare professionals identified trust as a critical but incompletely understood determinant of meaningful clinical implementation and highlighted persistent limitations in standardized measurement and cross study comparability [12]. Reliable assessment of trust and its cognitive and behavioral antecedents is therefore important not only for theoretical development but also for designing AI DSS that encourage appropriate rather than indiscriminate reliance. Reviews of trust measurement have identified multiple validated instruments while simultaneously demonstrating considerable inconsistency in how trust has been conceptualized and operationalized across studies [13]. General attitudes toward AI, measured through instruments that distinguish positive and negative evaluations, have also been systematically associated with personality characteristics and generalized trust, providing an additional individual difference perspective for understanding responses to specific AI DSS applications [14,15].

Despite substantial progress, an important empirical gap remains. Existing studies have frequently examined individual determinants of AI trust in isolation, making it difficult to determine their relative importance when multiple cognitive and behavioral factors operate simultaneously. In particular, limited evidence has integrated perceived transparency, algorithm aversion, anthropomorphism, need for cognition, general attitudes toward AI, perceived risk, and prior AI experience within a unified empirical model. This fragmentation is important because these factors may not exert independent and additive effects. For example, the potential trust enhancing effect of transparency may depend on users' preexisting resistance to algorithmic recommendations, while accumulated experience with AI systems may shape perceptions of their reliability, risk, and trustworthiness. Consequently, examining these determinants independently may obscure the conditional psychological mechanisms through which trust in AI DSS develops.

Addressing this gap is particularly important because increasing transparency alone may be insufficient to generate appropriately calibrated trust if users interpret algorithmic information through different cognitive dispositions and prior experiences. A more integrated approach is therefore required to determine not only which factors predict trust but also whether individual differences alter the effectiveness of commonly proposed trust building mechanisms. Such evidence can contribute to the development of AI DSS that communicate uncertainty and reasoning in ways that are understandable, contextually appropriate, and responsive to variation among users.

Accordingly, this study aimed to determine how cognitive and behavioral factors, particularly perceived transparency, algorithm aversion, anthropomorphism, need for cognition, general attitudes toward AI, perceived risk, and prior AI experience, individually

and interactively shaped public trust in artificial intelligence based decision support systems. Using a cross sectional survey of adults, the study integrated these factors within a single analytical framework to clarify their relative contributions to trust and to provide an empirical basis for designing AI DSS that support appropriately calibrated human reliance in consequential decision making contexts.

2. Materials and Methods

2.1. Participants and Procedure.

A total of 412 adults participated in a cross sectional, self administered online survey. Participants had a mean age of 34.82 years (SD = 10.05), with ages ranging from 18 to 70 years. The sample comprised 215 women (52.2%), 187 men (45.4%), and 10 participants (2.4%) who identified as nonbinary or another gender. Regarding educational attainment, 84 participants (20.4%) reported a high school education or lower, 204 (49.5%) held a bachelor's degree, and 124 (30.1%) held a graduate degree. Participants were also classified into three groups according to their self reported prior experience with AI based systems, including recommendation engines, chatbots, and automated screening tools. Of the total sample, 123 participants (29.9%) reported low experience, 186 (45.1%) reported moderate experience, and 103 (25.0%) reported high experience. Eligible participants were required to be at least 18 years of age. All participants provided informed consent before completing the survey. Participation was voluntary, and responses were collected anonymously to protect participants' privacy and confidentiality. The study protocol, including procedures for informed consent, data protection, confidentiality, and anonymization, was reviewed and approved by the authors' institutional research ethics committee before data collection.

2.2. Measures.

Trust in AI Decision Support Systems was assessed using a composite measure comprising items consistent with established trust in automation frameworks [1, 13]. The items captured participants' perceptions of system reliability and predictability, as well as their willingness to rely on recommendations generated by an AI DSS. Perceived Transparency was measured using items assessing the extent to which participants considered the reasoning underlying AI DSS outputs to be understandable and explainable, consistent with previous behavioral operationalizations of transparency [9]. Algorithm Aversion was assessed using items measuring participants' reluctance to rely on algorithmic recommendations relative to human judgment, based on established conceptualizations of algorithm aversion [6, 8]. Perceived Anthropomorphism was measured by assessing the extent to which participants attributed humanlike characteristics to the AI DSS. Need for Cognition reflected participants' general tendency to engage in and value effortful cognitive processing. Both constructs represented relevant characteristics of the human trustor identified in previous meta analytic research on trust in AI [3]. General Attitudes toward AI were assessed using items adapted from the two factor General Attitudes towards Artificial Intelligence Scale (GAAIS), generating separate scores for Positive Attitudes toward AI and Negative Attitudes toward AI [14, 15]. Perceived Risk was assessed using items that captured participants' subjective evaluations of the potential negative consequences associated with relying on an AI DSS. All items were assessed using seven point Likert type scales ranging from 1 (*strongly disagree/not at all*) to 7 (*strongly*

agree/extremely). Each construct score was calculated as the mean of four corresponding items, with higher scores indicating a greater level of the respective construct. Internal consistency was assessed using Cronbach's alpha. Alpha coefficients for all eight measures ranged from 0.87 to 0.89, demonstrating good internal consistency. The descriptive statistics and reliability coefficients for the study constructs.

2.3. Data Analytic Strategy.

Data were analyzed using Python with the NumPy, SciPy, and pandas packages. Prior to hypothesis testing, descriptive statistics and Cronbach's alpha coefficients were calculated for all study variables. Bivariate relationships between trust in AI DSS and the hypothesized cognitive and behavioral predictors were subsequently examined using Pearson product moment correlations. A three block hierarchical multiple regression analysis was conducted to determine the incremental contribution of cognitive and behavioral factors to trust in AI DSS. In Block 1, demographic variables comprising age, gender, and education were entered as covariates. In Block 2, perceived transparency, algorithm aversion, anthropomorphism, need for cognition, positive attitudes toward AI, negative attitudes toward AI, and perceived risk were added to determine their contribution to trust beyond demographic characteristics. In Block 3, the interaction between perceived transparency and algorithm aversion was introduced to determine whether algorithm aversion moderated the relationship between perceived transparency and trust in AI DSS.All continuous predictors were standardized using z scores before the regression analyses, and standardized regression coefficients (β) were reported to facilitate comparison of effect magnitudes across predictors. Changes in explained variance (ΔR^2) and the corresponding F change statistics were calculated at each step to determine whether the addition of each predictor block significantly improved model performance. The interaction effect was interpreted by examining whether the association between perceived transparency and trust varied according to the level of algorithm aversion. Finally, a one way analysis of variance (ANOVA) was conducted to examine whether trust in AI DSS differed according to participants' prior AI experience, categorized as low, moderate, or high. When significant group differences were identified, Bonferroni corrected pairwise comparisons were performed to determine which experience groups differed significantly. All statistical tests were two tailed, with the level of statistical significance established at $p < 0.05$.

3. Results and Discussion

3.1. Participant Characteristics.

The demographic and background characteristics of the 412 participants are summarized in Table 1. Women represented slightly more than half of the sample (52.2%), while men accounted for 45.4%, and 2.4% identified as nonbinary or another gender. Participants had a mean age of 34.82 years (SD = 10.05), with a broad age range of 18–70 years. Regarding educational attainment, approximately half of the participants held a bachelor's degree (49.5%), followed by a graduate degree (30.1%) and high school education or lower (20.4%). Prior experience with AI based systems also varied across the sample, with 45.1% reporting moderate experience, 29.9% reporting low experience, and 25.0% reporting high experience [1]. As shown in Table 1, the distribution across demographic and experience categories

provided sufficient variation for subsequent analyses of individual differences in trust and the potential influence of prior AI experience.

Table 1. Participant Demographic and Background Characteristics (N = 412).

Characteristic	Category	n	%
Gender	Female	215	52.2
	Male	187	45.4
	Nonbinary/Other	10	2.4
Age (years)	M = 34.82, SD = 10.05, range = 18–70	412	100.0
Education	High school or less	84	20.4
	Bachelor's degree	204	49.5
	Graduate degree	124	30.1
Prior AI experience	Low	123	29.9
	Moderate	186	45.1
	High	103	25.0

3.2. Descriptive Statistics and Reliability of Study Measures.

Descriptive statistics and internal consistency coefficients for the eight study constructs are presented in Table 2. Mean scores ranged from 4.53 to 4.65 on the seven point response scale, indicating that participants generally reported moderate levels of trust, transparency, algorithm aversion, anthropomorphism, need for cognition, attitudes toward AI, and perceived risk. The relatively similar mean values across constructs suggested that no single measure exhibited an extreme concentration toward either end of the response scale. Standard deviations ranged from 1.03 to 1.15, demonstrating sufficient interindividual variability to support subsequent correlational and multivariable analyses. Importantly, all measures demonstrated good internal consistency. As shown in Table 2, Cronbach's alpha coefficients ranged from .87 to .89, exceeding commonly accepted thresholds for adequate scale reliability. Trust in AI DSS demonstrated an alpha coefficient of .88, while the cognitive and behavioral predictors showed similarly strong reliability. These findings supported the use of the mean composite scores in subsequent correlation, regression, and moderation analyses [13–15].

Table 2. Descriptive Statistics and Reliability Of Study Measures.

Measure	M	SD	Cronbach's α
Trust in AI DSS	4.64	1.15	.88
Perceived Transparency	4.60	1.10	.88
Algorithm Aversion	4.59	1.08	.87
Perceived Anthropomorphism	4.53	1.03	.88
Need for Cognition	4.61	1.05	.89
Positive General Attitude (GAAIS+)	4.65	1.10	.88
Negative General Attitude (GAAIS−)	4.54	1.13	.89
Perceived Risk	4.57	1.05	.88

3.3. Bivariate Relationships Among Study Variables.

The bivariate relationships among trust in AI DSS and the seven cognitive and behavioral variables are presented in Table 3. Trust was significantly associated with all seven variables in the theoretically expected directions. The strongest positive association was observed between perceived transparency and trust ($r = .55$, $p < .001$), indicating that participants who perceived AI DSS decision processes as more understandable and explainable tended to report greater trust. Positive attitudes toward AI were also strongly associated with trust ($r = .48$, $p <$

.001), further indicating that broader favorable evaluations of AI were related to greater willingness to trust AI supported decisions. Conversely, perceived risk exhibited one of the strongest negative relationships with trust ($r = -.48$, $p < .001$), followed by negative attitudes toward AI ($r = -.44$, $p < .001$) and algorithm aversion ($r = -.41$, $p < .001$). These relationships indicated that participants who perceived greater risks or expressed stronger skepticism toward algorithmic systems were less likely to trust AI DSS. Anthropomorphism ($r = .24$, $p < .001$) and need for cognition ($r = .14$, $p < .01$) showed weaker but statistically significant positive relationships with trust. The correlations among the predictors also revealed theoretically meaningful patterns. As shown in Table 3, algorithm aversion was negatively associated with perceived transparency ($r = -.31$, $p < .001$) and positively associated with both perceived risk ($r = .36$, $p < .001$) and negative attitudes toward AI ($r = .48$, $p < .001$). Positive and negative attitudes toward AI were moderately inversely related ($r = -.50$, $p < .001$). Collectively, these patterns indicated that trust reflected multiple related but distinguishable cognitive and behavioral evaluations rather than a single generalized attitude toward technology [6, 8].

Table 3. Pearson Correlations Among Study Variables.

Variable	1	2	3	4	5	6	7
1. Trust in AI DSS	—						
2. Perceived Transparency	.55***	—					
3. Algorithm Aversion	−.41***	−.31***	—				
4. Anthropomorphism	.24***	.23***	−.03	—			
5. Need for Cognition	.14**	.08	−.06	.12*	—		
6. Positive Attitude	.48***	.30***	−.26***	.22***	.09	—	
7. Negative Attitude	−.44***	−.29***	.48***	−.09	−.02	−.50***	—
8. Perceived Risk	−.48***	−.29***	.36***	−.15**	−.02	−.39***	.42***

Note. Values represent Pearson's r. p < .05, p < .01, p < .001 (two tailed).

3.4. Predictors of Trust in AI Decision Support Systems.

The hierarchical multiple regression results are presented in Table 4. Demographic characteristics entered in Block 1 explained virtually no variance in trust ($R^2 = .00$), and the model was not statistically significant, $F(4, 407) = 0.10$, $p = .980$. This finding indicated that age, gender, and educational attainment were not meaningful predictors of trust when considered independently of participants' cognitive and behavioral characteristics. The addition of the seven cognitive and behavioral variables in Block 2 substantially improved the model, accounting for approximately 50% of the variance in trust ($\Delta R^2 = .50$), with a statistically significant improvement over the demographic model, $\Delta F(7, 400) = 56.59$, $p < .001$. As shown in Table 4, perceived transparency was the strongest positive predictor ($\beta = .34$, $p < .001$), followed by positive attitudes toward AI ($\beta = .20$, $p < .001$). Perceived risk emerged as the strongest negative predictor ($\beta = -.21$, $p < .001$), while algorithm aversion also independently predicted lower trust ($\beta = -.14$, $p < .01$). Need for cognition showed a smaller positive contribution ($\beta = .08$, $p < .05$). Anthropomorphism showed a positive but statistically nonsignificant association ($\beta = .07$, $p = .07$). These findings demonstrated that trust was explained considerably more strongly by participants' perceptions and cognitive and behavioral orientations toward AI than by their demographic characteristics.

Table 4. Hierarchical Regression Predicting Trust in AI DSS.

Predictor	Block 1 β	Block 2 β	Block 3 β
Age	−.02	−.02	−.02
Gender (female = 1)	.08	.09	.11
Education: graduate degree	.05	.08	.07
Education: high school or less	.02	.05	.02
Perceived Transparency	—	.34***	.35***
Algorithm Aversion	—	−.14**	−.14**
Perceived Anthropomorphism	—	.07	.07
Need for Cognition	—	.08*	.09*
Positive Attitude (GAAIS+)	—	.20***	.21***
Negative Attitude (GAAIS−)	—	−.08	−.08
Perceived Risk	—	−.21***	−.20***
Transparency × Algorithm Aversion	—	—	−.12***
R^2	.00	.50	.51
ΔR^2 (ΔF, df)	—	.50 (56.59, 7/400)***	.02 (12.54, 1/399)***

Note. β = standardized regression coefficient. $p < .05$, $p < .01$, $p < .001$. Dashes indicate that the predictor had not yet been entered into the model.

In Block 3, the interaction between perceived transparency and algorithm aversion was introduced to determine whether the relationship between transparency and trust depended on participants' level of algorithm aversion. The interaction produced a further statistically significant improvement in explained variance ($\Delta R^2 = .02$), $\Delta F(1, 399) = 12.54$, $p < .001$. The final model explained 51.4% of the variance in trust, $F(12, 399) = 35.16$, $p < .001$. Although the additional variance explained by the interaction was relatively modest, its statistical significance indicated that the association between transparency and trust was conditional rather than uniform across participants.

Specifically, the negative interaction coefficient ($\beta = -.12$, $p < .001$) indicated that algorithm aversion attenuated the positive relationship between perceived transparency and trust. The nature of this moderation effect is illustrated in Figure 1. Participants with low algorithm aversion demonstrated a substantially stronger positive relationship between transparency and trust, whereas this relationship was weaker among participants with high algorithm aversion. Thus, providing greater transparency may be particularly effective among users who are relatively receptive to algorithmic recommendations but less effective among those who already possess strong reservations about algorithmic decision making.

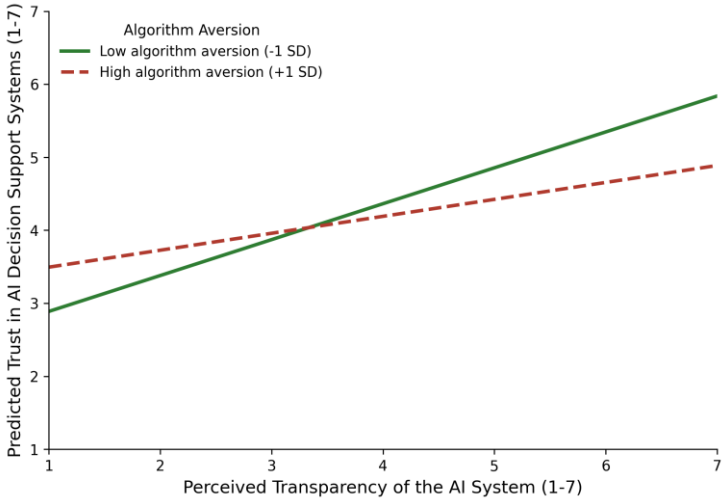


Figure 1. Moderating Effect of Algorithm Aversion on the Transparency–Trust Relationship.

This finding provides empirical support for the proposition that transparency alone may not be sufficient to establish trust in AI DSS. Previous research has similarly demonstrated that explanatory information can sometimes fail to increase, or may even reduce, trust when users experience difficulty interpreting algorithmic reasoning [9]. The present results extend this perspective by indicating that individual differences in algorithm aversion may condition the effectiveness of transparency independently of explanation format. This pattern is also compatible with evidence that the effects of AI explanations depend on users' cognitive processing characteristics [10]. From an applied perspective, transparency based interventions may therefore benefit from complementary design strategies that address baseline algorithmic skepticism, including opportunities for meaningful user control over system outputs [7].

As illustrated in Figure 1, the predicted trust scores increased with perceived transparency at both levels of algorithm aversion. However, the substantially steeper slope among participants with low algorithm aversion demonstrated that transparency exerted a stronger positive association with trust among individuals who were more receptive to algorithmic decision making. In contrast, the flatter slope among participants with high algorithm aversion indicated that increasing perceived transparency produced a comparatively smaller increase in trust. This visualization therefore reinforces the regression results by demonstrating that the effectiveness of transparency as a trust building mechanism depends partly on users' preexisting orientation toward algorithmic decision making.

3.5. Trust Differences According to Prior Experience with AI.

Trust in AI DSS differed significantly according to participants' prior experience with AI based systems, $F(2, 409) = 10.37$, $p < .001$, $\eta^2 = .048$. The effect size indicated that prior AI experience accounted for approximately 4.8% of the variance in trust, suggesting a modest but meaningful association between previous exposure to AI and subsequent trust. The descriptive statistics and pairwise comparisons are presented in Table 5.

Table 5. Trust in AI DSS by Prior AI Experience.

Experience Group	n	M	SD
Low	123	4.30	1.21
Moderate	186	4.67	1.06
High	103	4.98	1.13

Note: One way ANOVA: $F(2, 409) = 10.37$, $p < .001$, $\eta^2 = .048$. Bonferroni comparisons: Low vs. Moderate, $p = .016$; Low vs. High, $p < .001$; Moderate vs. High, $p = .057$.

As shown in Table 5, mean trust increased progressively across the three experience groups. Participants with low prior AI experience reported the lowest trust ($M = 4.30$, $SD = 1.21$), followed by participants with moderate experience ($M = 4.67$, $SD = 1.06$), while those with high experience reported the highest trust ($M = 4.98$, $SD = 1.13$). Bonferroni corrected pairwise comparisons showed that participants with low experience reported significantly lower trust than those with moderate experience ($p = .016$) and high experience ($p < .001$). However, the difference between the moderate and high experience groups did not reach statistical significance ($p = .057$). These results suggest that the most pronounced difference in trust occurred between participants with limited AI exposure and those with greater experience, rather than through equivalent increases at each successive level of experience. This pattern is consistent with evidence indicating that direct familiarity with AI technologies is associated with more favorable attitudes toward their use and governance [2] and with meta analytic

findings identifying prior experience and interaction history as important human trustor characteristics associated with trust in automated and AI based systems [4, 5].

The experience related pattern in trust is further illustrated in Figure 2. Mean trust generally increased from low to moderate and high levels of AI experience across the educational groups. This pattern suggests that prior interaction with AI systems may be more closely associated with trust than educational attainment alone. However, because the study was cross sectional, the observed relationship should not be interpreted as evidence that AI experience directly caused higher trust. Individuals who initially held more favorable attitudes toward AI may also have been more likely to engage with AI based technologies. Nevertheless, the pattern supports the importance of considering direct technological experience when examining individual differences in trust [4, 5]. Together with the moderation results, these findings suggest that opportunities for structured and low risk interaction with AI DSS may complement appropriately designed transparency mechanisms, particularly when differences in users' baseline algorithm aversion are considered [6, 11].

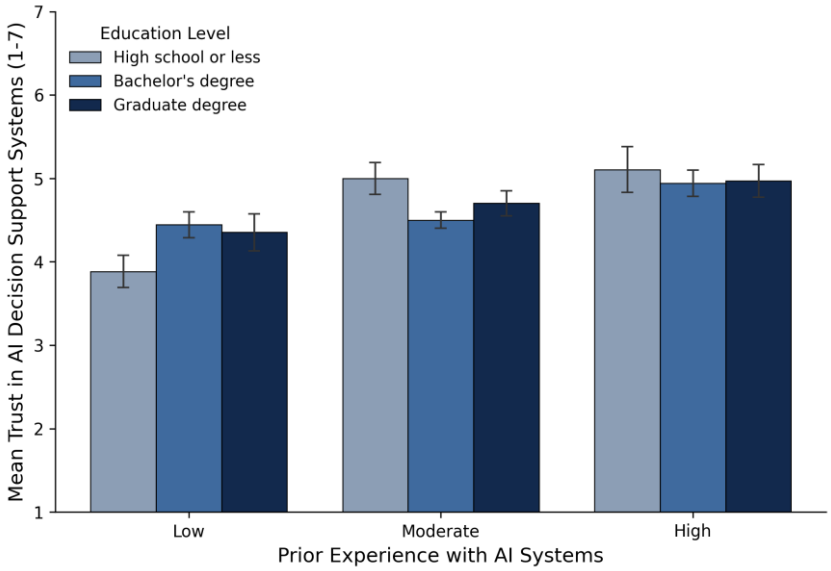


Figure 2. Trust in AI DSS by Prior AI Experience and Education.

3.6. Integrative Discussion.

The findings provide empirical support for a cognitive and behavioral account of public trust in AI DSS in which trust reflects the combined influence of perceived system characteristics, individual dispositions, risk perceptions, general attitudes toward AI, and accumulated technological experience. This interpretation is consistent with the broader trustor, trustee, and context framework used to conceptualize trust in automated and AI based systems [1,3]. Importantly, demographic characteristics explained virtually no variance in trust, whereas the cognitive and behavioral variables accounted for approximately half of the observed variance. This contrast indicates that understanding how individuals perceive and evaluate AI may be more informative for explaining trust than basic demographic characteristics alone.

Perceived transparency emerged as the strongest positive predictor of trust, emphasizing the importance of users being able to understand how AI DSS generate or communicate their recommendations. However, the significant interaction between transparency and algorithm aversion demonstrated that this relationship was conditional. The positive association between

transparency and trust weakened as algorithm aversion increased. Thus, transparency should not be interpreted as a universally effective mechanism for increasing trust. Rather, its effectiveness appears to depend partly on users' preexisting orientation toward algorithmic decision making. This finding complements previous evidence showing that transparency may produce variable trust outcomes depending on how explanations are presented and cognitively processed [9,10].

Perceived risk and positive attitudes toward AI also made substantial independent contributions to trust, whereas algorithm aversion remained a significant negative predictor after the other cognitive and behavioral variables were considered simultaneously. These findings demonstrate that trust cannot be explained solely by perceptions of technical transparency or system performance. Users also evaluate the potential consequences of reliance and approach AI systems with broader preexisting attitudes and expectations. Consequently, strategies intended to promote appropriately calibrated trust should address both cognitive understanding and perceived risk rather than focusing exclusively on system accuracy or explainability [2,12].

Prior AI experience provided an additional dimension to this pattern. Participants with moderate and high experience reported greater trust than participants with limited experience, although the difference between moderate and high experience was not statistically significant. This finding suggests that familiarity with AI may be associated with trust particularly when distinguishing relatively inexperienced users from those who have already accumulated meaningful exposure. Nevertheless, the cross sectional design does not establish whether experience increases trust or whether individuals who already trust AI are more likely to use such technologies. Longitudinal and experimental studies are therefore required to establish the direction of this relationship.

The findings have practical implications for AI DSS deployed in consequential domains such as healthcare, finance, human resource management, and public administration, where appropriate reliance is essential [2,12]. A uniform transparency strategy may be insufficient because users differ in algorithm aversion, risk perception, general attitudes, and prior experience. Developers and implementing organizations should therefore consider explanation strategies that are understandable and context appropriate while providing users with structured opportunities to become familiar with system capabilities and limitations. Limited user control and supervised interaction may also help users develop more appropriately calibrated expectations of algorithmic systems [7,11]. Importantly, the objective should not be to maximize trust indiscriminately, but to support trust that corresponds appropriately to the actual reliability, limitations, and uncertainty of the AI DSS.

Several limitations should be considered when interpreting these findings. First, the cross sectional design prevented causal conclusions regarding the relationships among transparency, algorithm aversion, experience, and trust. Second, reliance on self reported measures introduced the possibility of common method and social desirability biases. Third, the study examined generalized perceptions of AI DSS rather than behavioral reliance on a specific system within a real high stakes decision environment. Future studies should therefore employ longitudinal and experimental designs, incorporate behavioral measures of reliance, manipulate transparency and user experience under controlled conditions, and examine whether the observed relationships remain consistent across specific AI DSS applications.

Research involving more demographically and culturally diverse populations would also help determine the generalizability of the proposed cognitive and behavioral framework [12,13]

Conclusion

This study demonstrates that public trust in artificial intelligence based decision support systems (AI DSS) is shaped primarily by an interconnected set of cognitive, behavioral, and experiential factors rather than by demographic characteristics alone. Perceived transparency emerged as the strongest positive predictor of trust, whereas perceived risk and algorithm aversion were important negative predictors. Positive attitudes toward AI and need for cognition also contributed to trust, highlighting the importance of individual cognitive orientations in shaping responses to AI assisted decision making. Importantly, the positive association between perceived transparency and trust weakened as algorithm aversion increased, demonstrating that greater explainability does not necessarily produce equivalent trust benefits across users. Prior experience with AI was also associated with higher levels of trust, particularly when participants with limited experience were compared with those reporting moderate or high experience. Collectively, these findings indicate that transparency alone is insufficient to establish appropriately calibrated trust in AI DSS. Effective system design should integrate understandable and context appropriate explanations with clear risk communication, meaningful user control, and opportunities for structured interaction that enable users to develop realistic expectations regarding system capabilities and limitations. The findings therefore support a user centered approach in which trust is developed through the combined consideration of system characteristics and individual differences rather than through uniform transparency strategies. Nevertheless, the cross sectional design and reliance on self reported measures limit causal interpretation and do not establish whether greater AI experience increases trust or whether individuals with greater initial trust are more likely to engage with AI technologies. Future research should employ longitudinal and experimental designs, behavioral measures of actual reliance, more demographically and culturally diverse populations, and application specific AI DSS scenarios to determine how transparency, algorithm aversion, perceived risk, and accumulated experience interact over time. Such evidence will be essential for developing AI DSS that promote not simply greater trust, but appropriately calibrated reliance in consequential decision making contexts.

Competing Interests.

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

Author Contributions.

Both authors contributed equally to the conceptualization, study design, data analysis, and writing of this manuscript. Both authors read and approved the final version of the manuscript.

Data Availability Statement.

The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request.

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