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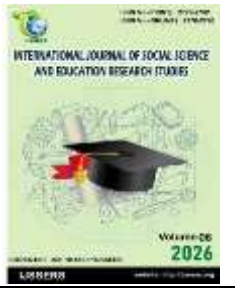

What Does Not Predict AI Adoption: A Pilot Cross-Sectional Study

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ABSTRACT

This pilot cross-sectional study examined the extent to which perceived resilience, mindset orientation, and demographic variables are associated with attitudes toward artificial intelligence (AI) adoption. Using a quantitative, cross-sectional design, secondary data from 88 adult participants were analyzed. Participants completed measures of AI attitudes (AIAS-4), perceived resilience (Brief Resilience Scale), and mindset orientation (adapted Theories of Intelligence Scale), along with demographic variables including age, biological sex, and education. Descriptive analyses indicated generally favorable attitudes toward AI, moderate to high levels of resilience, and a tendency toward growth-oriented mindset characteristics. Pearson correlation analyses revealed weak associations between AI attitudes and resilience, mindset, and age. Independent samples t-tests indicated no significant differences in resilience or mindset across sex; however, a statistically significant difference in AI attitudes was observed, with male participants reporting higher AI adoption scores than female participants. One-way analyses of variance demonstrated no significant differences in AI attitudes or resilience across educational levels or mindset categories. A small but statistically significant difference was observed in mindset orientation across education levels. Multiple regression analysis indicated that resilience, mindset, and age did not significantly predict AI attitudes, accounting for a minimal proportion of variance. Overall, findings suggest that attitudes toward AI adoption are not strongly explained by general psychological traits or most demographic variables. These results highlight the potential importance of domain-specific factors, such as experience with AI, perceived utility, and contextual exposure, as potential predictors of AI adoption attitudes. Future research should explore these factors using longitudinal and experimentally informed designs.

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KEYWORDS:
Artificial Intelligence Adoption, Psychology Resiliency, Mindset.

1. INTRODUCTION

Artificial intelligence adoption has often been studied through the lenses of technology acceptance, innovation diffusion, and organizational readiness. Across that literature, the most common predictors are not broad personality-like traits, but factors such as trust, security, cost, social influence, perceived utility, prior experience, technical competence, management support, strategic road mapping, and digital maturity (Radhakrishnan & Chattopadhyay, 2022). Reviews of AI adoption research further show that dominant explanatory frameworks include the Technology-Organization-Environment framework, Diffusion of Innovation, UTAUT, and TAM, all of which place substantial emphasis on contextual, structural, and perception-based determinants of adoption rather than on generalized psychological strengths such as resilience or mindset alone (Radhakrishnan & Chattopadhyay, 2022). This matters for the present study because it suggests that while resilience and mindset may be theoretically relevant, they are entering a literature in which AI adoption is usually explained through domain-specific beliefs and conditions.

Recent work on AI adoption also indicates that adoption is not a single individual decision, but often a process embedded in broader systems. Agrawal, Gans, and Goldfarb (2022) argue that AI adoption may require system-wide organizational change because tasks and decisions are interdependent, meaning adoption is shaped by system structure rather than isolated individual willingness. Similarly, Neumann, Guirguis, and Steiner (2024) found that technological and organizational factors vary in importance depending on the stage of adoption within public organizations, further reinforcing the role of contextual and structural influences. Taken together, these studies suggest that willingness to adopt AI may be shaped by stage, setting,

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and implementation environment as much as by internal characteristics of the user.

Resilience theory offers one reason to expect a positive relationship between resilience and AI adoption attitudes. Contemporary resilience scholarship increasingly defines resilience not as a static trait, but as a process of adaptation in the face of adversity, disruption, or challenge (Van Breda, 2018). Van Breda (2018) distinguished resilience-as-outcome from resilience-as-process and argues that the process definition is more appropriate when examining how individuals respond to challenges. Howard, et al (2022) and Howard, et al (2023) echoed Van Breda's (2018) established process-oriented definition of resilience demonstrating a common thread in the ability to improve resilience rather than a fixed end-state. In that framing, resilience involves dynamic processes that support adaptation and functioning under stress. This logic can be extended to AI adoption: if engaging with AI involves uncertainty, ambiguity, and perceived risk, then individuals with higher perceived resilience may be more likely to respond with adaptive engagement rather than avoidance.

At the same time, resilience theory also provides reasons to be cautious about predicting AI attitudes from individual-level resilience alone. Van Breda (2018) emphasizes that resilience is not solely an internal attribute but is influenced by social, ecological, and contextual systems. This suggests that resilience operates through interactions between the individual and their environment rather than as a purely internal disposition. For the present study, this is critical because a self-report measure of resilience may not capture the broader contextual support that influence behavior, particularly in technology adoption settings.

Related intervention-based research supports the idea that resilience can influence behavior and performance. In two separate military sample, resilience training was associated with statistically significant improvements in perceived resilience and the application of resilience-related skills such as goal setting and emotional control or healthy behavior change adoption (Howard, et al., 2022; Howard, et al., 2023). This work frames resilience as a modifiable construct that can influence behavior under stress and uncertainty. These findings align with the conceptualization of resilience as supporting adaptive action, suggesting that individuals with higher resilience may be more capable of engaging with unfamiliar or complex technologies such as AI.

Mindset theory provides a second theoretical pathway linking individual psychology to AI adoption attitudes. Growth mindset theory posits that individuals who believe abilities can be developed are more likely to engage in challenge-seeking behavior, persist through difficulty, and adopt learning-oriented strategies (Burnette, et al., 2022a; Burnette, et al., 2022b; Dweck, 2006). These characteristics make mindset a plausible predictor of willingness to engage with emerging technologies. A growth-oriented individual may be more inclined to experiment with AI tools, tolerate initial difficulty, and view AI-related skill acquisition as attainable.

However, the growth mindset literature also suggests that such effects are not universally strong or consistent. Burnette and colleagues (2022b) highlight that the effectiveness of growth mindset interventions varies depending on context, implementation fidelity, and individual differences. Furthermore, meta-analytic findings indicate that mindset effects can be modest and heterogeneous across domains, suggesting that mindset alone may not strongly predict complex behaviors in all settings (Burnette, et al., 2022a). These findings support a more cautious expectation that mindset may influence behavior but not necessarily serve as a primary determinant of AI adoption attitudes. The variance in suggested effects of mindset, identified mindset as a worthy candidate for inclusion in the exploration of determinants of AI adoption.

Taken together, the literature supports the rationale for examining resilience and mindset as potential predictors of AI attitudes while also highlighting their likely limitations. Resilience and mindset both provide theoretical mechanisms related to adaptation, persistence, and willingness to engage with challenge. However, the broader AI adoption literature consistently emphasizes domain-specific factors such as perceived usefulness, trust, exposure, and contextual constraints as primary drivers of adoption behavior (Agrawal, Gans, & Goldfarb, 2022; Neuman, Guirguis, & Steiner, 2024; Radhakrishnan & Chattopadhyay, 2022). The present study therefore addresses an important gap by empirically testing whether general psychological constructs associated with adaptation meaningfully relate to AI adoption attitudes, or whether such attitudes are better explained by more context-specific determinants.

RESEARCH QUESTIONS

This investigation was guided by the following research questions:

1. Is there a statistically significant association between attitudes toward artificial intelligence adoption and perceived resilience in adults?
2. Is there a statistically significant association between attitudes toward artificial intelligence adoption and mindset orientation on the fixed-to-growth continuum?
3. Do demographic variables such as age, biological sex, and educational attainment show statistically significant relationships with attitudes toward artificial intelligence adoption?

HYPOTHESES

The below listed hypotheses were tested at the 0.05 significance level.

1. There is a statistically significant association between attitudes toward artificial intelligence adoption and perceived resilience in adults.
2. There is a statistically significant association between attitudes toward artificial intelligence adoption and mindset orientation on the fixed-to-growth continuum.
3. At least one demographic variable (age, biological sex, or educational attainment) is significantly associated with attitudes toward artificial intelligence adoption.

II. METHODOLOGY

Study Design

This pilot study adopted a quantitative, cross-sectional, ex post facto design to examine preliminary associative relationships between perception of resilience, mindset orientation, and attitudes toward adoption of artificial intelligence (AI). This non-experimental design did not involve the manipulation of variables or randomized assignment to either a control or intervention group. Rather, the design assessed naturally occurring differences in participants' self-reported perceptions at a single-time point using secondary data analysis of voluntarily provided data from another project. Thus, the ex post facto study was intended to identify patterns of concurrent association among constructs rather than establish causal or predictive relationships. Findings from the pilot investigation were intended to inform the feasibility, refinement, and potential expansion for future longitudinal or multivariate research aimed at deeper examination of the effects on variables across time and various modal interventions. This study involved retrospective collection of de-identified data from adult contributors to other research that was anonymously reported using minimal risk survey procedures. Based on the pre-existence of the data analyzed, the minimal risk of survey data, and the absence of direct identifiers and sensitive personal data of the contributing sample, this project met criteria for exempt research. All data from this study was maintained in secure storage in accordance with standard research practices.

Participants and Collection

A total of 89 participants voluntarily enrolled in the study, with an age range of 21 to 68 years old (mean age was 41.1 years old). One survey was rejected due to not meeting all inclusion requirements, making the sample size N=88. The sample was sourced from secondary data collected from a combination of social media posts and group links for survey taking websites, this resulted in the sample population consisting of 63 participants self-reported male sex (71.59% of sample), and 25 participants self-reporting as female sex (28.41% of population).

Inclusion criteria for the study included willingness to participate in the 10-minute and 20-questions combination survey, agreeing to voluntarily participate through the survey consent form, being over 18-years old, and full completion of the survey. Participants were asked to fully and truthfully complete the surveys, while paying attention to reverse coding in questionnaires. The study involved minimal risk survey procedures and was specifically designed to protect privacy through non-identifiable data collection and secure data handling. All data was de-identified by requiring anonymous responses over the internet and the collection of minimal and basic information for data collection, age, education-level, biological sex, and ethnicity.

Sample Description

The sample's (N=88) descriptive characteristics consist of ethnicity breakdown, biological sex breakdown, age breakdown, and education breakdown. The sample's ethnicity breakdown consists of 64 Caucasians/White non-Hispanic (72.73%), 7 African Americans (7.95%), 16 Hispanics (18.18%), and 1 of Middle Eastern descent (1.14%). The sample was primarily male 71.59% of respondents (N=63) while females made up 28.41% of respondents (N=25). The ages of participants ranged from 21 to 68 years old with a mean age of 41.1 years old. The educational description consisted of 3 members of the sample having a High-school diploma or GED (3.4%), 29 sample respondents having some college or having earned an Associates Degree (32.95%), 28 respondents having earned a Bachelors Degree (31.82%), 6 sample respondents being in Grad School or having earned a Post-Grad Certificate (6.82%), 13 respondents having earned a Masters Degree (14.77%), 1 respondent being in the Doctoral process as either a student, candidate, or being ABD status (1.14%), and 8 respondents to the surveys having earned a Doctoral Degree (9.09%). These data are represented visually in Table 1 for ease of digestion. This indicates that the sample, while diverse across demographic variables, was primarily composed of college-educated, non-Hispanic White males over the age of 40 (n = 34, 38.64%). Thusly, this sample limits the strength of external validity of findings to predict outcomes of broader and more diverse groups.

Questionnaires

Aside from descriptive data, the study examined the sample through the lens of three quantitative surveys. The surveys included in the study were the Artificial Intelligence Attitudes Survey (AIAS-4) to gauge attitudes toward AI adoption and intended usage; the Ohio State University's Brief Resilience Scale (BRS) to examine self-reported perception of resilience; and the Mindset Quiz (MQ) a small-form factor adoption from Carol Dweck's (2006) Theories of Intelligence Survey (TIS).

The AIAS-4 is a four-item instrument assessing attitudes toward AI adoption and perceived beneficence of AI adoption, measured on a 10-point Likert scale. Previous validation studies demonstrated good to excellent internal consistency ($\alpha = 0.86 – 0.93$) from various ethnic populations, both biological sexes, and age ranges 18-81 years old (Grassini, 2023; Talik, Talik, & Grassini, 2025; Kose, Simsek, & Demir, 2025).

The BRS is a six-item instrument assessing overall perception of resilience and has been positively correlated to positive affect and optimism while being negatively correlated to pessimism and negative affect, measured on a 5-point Likert scale that include reverse coded items. Previous validation studies demonstrated good to excellent internal consistency ($\alpha = 0.81 – 0.91$) from various ethnic populations, both biological sexes, and age ranges 18-88 years old (Smith, et al. 2008; Konaszewski, Niesiobedezka, Surzykiewics, 2020; Sanchez, et al. 2021).

The MQ is a ten-item instrument adapted from the TIS and aligned for ease of population understanding assessing overall orientation of mindset on a sliding scale from strong fixed mindset to strong growth mindset based on total score, measured on a 4-point Likert scale that include reverse coded items. Previous validation studies on the surveys for which this was adopted demonstrated acceptable to good internal consistency ($\alpha = 0.67 – 0.89$) from various ethnic populations, both biological sexes, and age ranges 14-85 years old (Ortiz Alvardo, et al. 2022; Sigmundsson & Hoga, 2024; Kholili, et al. 2025). Internal consistency for all measures was evaluated within the current sample. Based on prior validation evidence and study design, these instruments were appropriate for examining the targeted constructs in this pilot investigation.

Internal consistency reliability was assessed for each instrument within the current sample. Cronbach's alpha coefficients were as follows: AIAS-4 ($\alpha = 0.91$), BRS ($\alpha = 0.83$), and MQ ($\alpha = 0.73$), indicating excellent, good, and acceptable internal consistency reliability, respectively. These values are consistent with previously reported reliability estimates for each instrument.

Statistical Analysis

Descriptive statistics were calculated for all study variables. Pearson correlations were conducted to examine associations between AI attitudes, resilience, mindset, and age. Independent samples t-tests were used to assess group differences based on binary variables, such as gender. Independent samples t-tests were conducted using Welch's correction for unequal variances, which produces adjusted degrees of freedom. One-way ANOVA tests were conducted to examine differences across multi-level categorical variables (e.g., education level, mindset categories). A multiple linear regression analysis was performed to evaluate the extent to which resilience, mindset, and age predicted AI attitudes. Statistical significance was set at $\alpha = 0.05$. All analyses were conducted using Microsoft Excel (Microsoft 365) Data Analysis Add-In and outcomes and results were cross-validated manually.

III. RESULTS

Descriptive statistics were computed for all primary study variables ($N = 88$) and are visualized in Table 2. Participant age ranged from 21 to 68 years ($M = 41.10$, $SD = 8.38$), with a median of 41, indicating a middle-aged sample with moderate variability. Attitudes toward artificial intelligence (AI) adoption ranged from 1 to 10 ($M = 7.04$, $SD = 2.11$, Median = 7.5), reflecting generally favorable perceptions of AI. The distribution demonstrated moderate negative skew (-0.84) and near-normal kurtosis (0.09), indicating slight clustering toward higher values without substantial deviation from normality.

Perceived resilience (BRS) scores ranged from 2 to 5 ($M = 3.91$, $SD = 0.77$, Median = 4), suggesting moderate to high resilience within the sample. The distribution exhibited mild negative skew (-0.53) and slight platykurtosis (-0.17). Mindset orientation scores ranged from 12 to 30 ($M = 24.70$, $SD = 3.94$, Median = 25.5), indicating a general tendency toward a growth-oriented mindset. These scores also demonstrated moderate negative skew (-0.73) and near-normal kurtosis (0.11). Across all variables, skewness and kurtosis values fell within acceptable thresholds for approximate normality ($|\text{skew}| < 1$, $|\text{kurtosis}| < 1$), supporting the use of parametric analyses.

A Pearson Correlation Matrix was conducted and is visualized in Table 3. Pearson correlation analyses were conducted to examine relationships among age, AI attitudes, perceived resilience, and mindset orientation. AI attitudes were weakly and negatively associated with age ($r = -0.20$), indicating a slight tendency for younger participants to report more favorable attitudes toward AI. AI attitudes also demonstrated weak positive associations with resilience ($r = 0.11$) and mindset orientation ($r = 0.13$), suggesting minimal relationships between these psychological variables and AI adoption attitudes. In contrast, resilience and mindset orientation were moderately positively correlated ($r = 0.28$), indicating that individuals with higher resilience tended to report more growth-oriented mindset characteristics.

Independent samples t-tests were conducted to examine differences between male and female participants across mindset orientation, AI attitudes, and resilience. No statistically significant differences were observed for mindset orientation, $t(49) = -1.03$, $p = 0.31$, or resilience, $t(41) \approx 0.97$, $p = 0.34$. However, a statistically significant difference was found for AI attitudes, with male participants ($M = 7.48$) reporting higher AI adoption scores than female participants ($M = 5.91$), $t(35) = 2.96$, $p = 0.005$.

A series of one-way analyses of variance (ANOVA) were conducted to examine group differences across education level and categorized mindset groups. No statistically significant differences in AI attitudes were observed across education levels, $F(5, 82) = 0.24$, $p = 0.94$, or across mindset categories (fixed, mixed, growth), $F(2, 85) = 0.22$, $p = 0.80$. Similarly, education level was not significantly associated with perceived resilience, $F(5, 82) = 0.34$, $p = 0.88$.

A statistically significant difference was observed in mindset orientation across education levels, $F(5, 82) = 2.33$, $p = 0.049$, indicating that mindset scores varied by educational attainment. Given the borderline level of

significance and unequal group sizes, this finding should be interpreted with caution.

A multiple linear regression analysis was conducted to examine the extent to which perceived resilience, mindset orientation, and age predicted AI attitudes. The overall model was not statistically significant, $F(3, 84) = 1.78$, $p = 0.157$, and explained a small proportion of variance in AI attitudes ($R^2 = 0.06$, adjusted $R^2 = 0.03$). None of the individual predictors significantly contributed to the model. Resilience ($\beta = 0.19$, $p = 0.53$) and mindset ($\beta = 0.06$, $p = 0.32$) were not significant predictors, while age demonstrated a negative but non-significant relationship with AI attitudes ($\beta = -0.05$, $p = 0.073$).

IV. DISCUSSION

The purpose of this pilot cross-sectional study was to examine the extent to which perceived resilience, mindset orientation, and demographic variables were associated with attitudes toward artificial intelligence (AI) adoption. Overall, the findings indicate that psychological constructs such as resilience and mindset, as well as most demographic variables, were not significantly associated with AI attitudes within the present sample. Contrary to expectations, neither resilience nor mindset orientation demonstrated meaningful relationships with AI adoption attitudes. These findings were consistent across multiple analytical approaches, including correlation, group comparisons, and regression modeling. The convergence of null results across methods strengthens confidence in the conclusion that general psychological traits, such as resilience and mindset, may not play a central role in shaping attitudes toward AI adoption. Importantly, these findings occurred despite strong internal consistency in the primary outcome measure (AIAS-4 $\alpha = 0.91$) and good reliability in resilience (BRS $\alpha = 0.83$), suggesting that the absence of meaningful associations is unlikely to be solely attributable to measurement instability. While the mindset measure demonstrated acceptable reliability ($\alpha = 0.73$), which may attenuate weaker relationships, the consistency of null findings across multiple analytical approaches indicates that general psychological constructs may have limited explanatory power in predicting AI adoption attitudes within this sample. Given that measurement reliability places an upper bound on observable correlations, the strong reliability of the AI attitudes measure suggests that the lack of meaningful associations is unlikely to be fully explained by measurement error alone.

Similarly, the educational attainment variable did not demonstrate significant relationships with AI attitudes. These findings challenge common assumptions that higher education or advanced cognitive frameworks, such as a growth mindset, are directly associated with greater acceptance of emerging technologies. Instead, the results suggest that attitudes toward AI may be more uniformly distributed across individuals than previously assumed.

One notable exception was the presence of a statistically significant difference in AI attitudes between male and female participants, with male participants reporting higher levels of AI adoption attitudes. This finding suggests that sex-based differences may influence perceptions of AI, although the underlying mechanisms remain unclear. Possible explanations may include differences in technology exposure, occupational experiences, or confidence in interacting with emerging technologies, though these factors were not directly measured in the present study. Additionally, age demonstrated a small, non-significant trend indicating that younger participants may hold slightly more favorable attitudes toward AI. While this relationship did not reach statistical significance in the regression model, it aligns with broader literature suggesting generational differences in technology adoption and familiarity. Taken together, these findings suggest that attitudes toward AI adoption are not strongly explained by broad psychological traits or traditional demographic variables. Instead, AI attitudes may be influenced by more domain-specific factors, such as direct experience with AI systems, perceived usefulness, trust in technology, or contextual exposure.

Importantly, these convergent null findings represent a meaningful contribution to the literature. Rather than indicating a lack of effect, these results suggest that commonly assumed predictors, such as mindset and resilience, may have limited explanatory value in this domain.

V. CONCLUSION

This pilot cross-sectional study highlights the need for future research to move beyond general psychological constructs and instead examine more targeted predictors of AI adoption, including technological literacy, prior exposure, and context-specific attitudes. Future research should also consider more diverse and balanced samples, particularly with respect to sex and educational subgroups, as well as the use of longitudinal designs to assess how attitudes toward AI evolve over time. Additionally, the inclusion of interaction effects and moderation analyses may help clarify whether demographic variables influence AI attitudes under specific conditions rather than in direct, independent ways.

Notably, several limitations should be considered when interpreting the present findings. The unequal subgroup sizes and reliance on self-reported measures may influence the stability and generalizability of results. Although internal consistency reliability for the instruments was within acceptable to excellent ranges (AIAS-4 $\alpha = 0.91$; BRS $\alpha = 0.83$; MQ $\alpha = 0.73$), the comparatively lower reliability of the mindset measure may have introduced measurement error, potentially attenuating observed relationships with AI attitudes. As measurement error increases, the ability to detect true associations is reduced, which may contribute to the weak or non-significant findings observed in this study. This pilot study may be underpowered to detect small effect

sizes, particularly given the modest sample size and subgroup imbalances, and therefore non-significant findings should be interpreted with caution rather than as definitive evidence of no relationship.

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VII. DISCLOSURE

The author reports no conflicts of interest in this work.

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