Journal of Statistics Applications & Probability
An International Journal

http://dx.doi.org/10.18576/jsap/150609

Innovative Personality and Attitudes Toward Artificial Intelligence Among Students at a University in Saudi Arabia

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Received: 10 Aug. 2026, Revised: 7 Oct. 2026, Accepted: 26 Oct. 2026
Published online: 1 Nov. 2026

Abstract: In this study, we examined the associations between innovative personality and positive and negative attitudes toward artificial intelligence among students at a University in Saudi Arabia. This cross-sectional study examined associations between innovative personality and positive and negative attitudes toward artificial intelligence among 438 students aged 18–24 years at a Saudi university. Participants completed an Arabic adaptation of an innovative-personality instrument and the General Attitudes towards Artificial Intelligence Scale; an independent pilot involved 100 students. Analyses emphasized effect sizes, confidence intervals, multiplicity control, and the distinction between concurrent association and prospective prediction. Overall innovative personality correlated positively with favorable AI attitudes, r = .226, 95% CI [.135, .313], and negatively with the negative-attitude score, r = −.187, 95% CI [−.276, −.095]. In the simultaneous model, the two attitudes accounted for 6.2% of personality-score variance, with standardized coefficients of .180 and −.114, respectively. Gender contrasts were small and did not provide evidence of a difference. Science students reported more favorable AI attitudes than humanities students before adjustment, but this contrast did not survive correction across the six principal demographic comparisons. The score distribution indicated endorsement above the response midpoint, which does not establish the prevalence of innovative individuals or actual creative achievement. These findings position AI attitudes as modest correlates of students' innovative self-perceptions. They support investigating critical and exploratory engagement with AI while leaving the effects of actual AI use, instructional design, and sustained creative development to longitudinal and experimental research.

Keywords: innovative personality; artificial intelligence attitudes; creativity; university students; Saudi Arabia; measurement

1 Introduction

Universities face a psychological question alongside the practical challenge of integrating artificial intelligence: which students approach these technologies as opportunities for exploration, and how do those orientations relate to their perceptions of themselves as innovative people? The question matters because enthusiasm for a tool, willingness to experiment, and the capacity to produce valuable original work are related possibilities rather than interchangeable outcomes. A student may welcome AI without using it effectively, question its reliability while employing it skillfully, or produce strong creative work without relying on it. Research that distinguishes these possibilities can contribute more to educational decisions than a general claim that technology improves innovation.

Creative performance involves originality and effectiveness, evaluated in relation to a task and its context (Runco & Jaeger, 2012). Self-reported innovative personality instead concerns perceived dispositions that may support exploration, initiative, and the expression of new ideas. Assessing such dispositions is useful, but it does not replace the evaluation of products or performances by appropriate judges, as emphasized in the consensual assessment tradition (Amabile, 1982). This distinction is especially consequential in AI research, where fluent generated output can be mistaken for evidence that a user has developed an enduring creative capacity.

The educational literature documents a broadening range of AI applications, including adaptive instruction, assessment, and support for student learning (Zawacki-Richter et al., 2019; Crompton & Burke, 2023). Reviews also identify persistent questions about pedagogy, evaluation, and the conditions under which educational benefits occur (Chiu et al.,

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2023). Large language models make these questions particularly visible because the same interface can assist idea generation, explanation, writing, and revision while introducing errors or encouraging superficial acceptance of plausible responses (Kasneci et al., 2023). Consequently, attitudes toward AI deserve attention as psychological orientations, without being treated as direct measures of instructional effectiveness.

The present study examines this issue in a Saudi university sample. It retains the distinction between positive evaluations of AI and concerns about AI and relates both to innovative-personality scores. The focus is deliberately local: students from one institution provide evidence about associations within that setting, while the broader theoretical questions concern university learning across contexts. Saudi relevance follows from the institutional setting and the educational interest in developing students' initiative and judgment; it does not imply that one sample represents Saudi society or universities worldwide.

Three features shape the contribution. First, the study evaluates attitudes rather than substituting them for actual AI use. Second, it treats innovative personality as a self-report construct rather than a performance-based creativity outcome. Third, it prioritizes the size, uncertainty, and scope of associations over a binary division into significant and nonsignificant findings. These choices connect a context-specific survey to broader discussions of measurement transparency and responsible psychological inference (Flake & Fried, 2020; Wasserstein & Lazar, 2016).

2 Conceptual Framework

2.1 Innovative Personality as a Self Reported Disposition

Personality research suggests that characteristics associated with exploration and openness are relevant to creativity, although their importance depends on the criterion used. Feist's (1998) synthesis of scientific and artistic creativity illustrates the need to consider domain and achievement criteria. Karwowski and Lebuda (2016) further distinguish creative self-beliefs from other creativity indicators when examining their relationships with personality. A person's confidence in being creative is psychologically meaningful, but it cannot by itself establish the originality or usefulness of the person's work.

The instrument adapted in this study organizes innovative personality around leadership, openness, and courage. Othman (2016) developed the underlying framework in a Malaysian teacher population and examined successive versions of its item structure. The current application concerns an Arabic student adaptation, not an unchanged administration of the final teacher instrument. This distinction limits the transfer of previous validity evidence. The local interpretation concerns perceived initiative, receptiveness to ideas, and willingness to express or pursue a position; it does not establish managerial leadership or actual risk-taking behavior.

Leadership is relevant because new ideas often require articulation and coordination. Openness concerns receptiveness to unfamiliar perspectives, while courage concerns willingness to act or speak despite uncertainty. These dimensions provide a framework for examining innovative self-perceptions, but their labels should not be taken as proof that they are identical to established Big Five traits or to behavioral measures of creative performance. The composite is therefore interpreted narrowly as an index of the dispositions represented by its items.

2.2 Positive Evaluations and Concerns About Artificial Intelligence

Technology acceptance research distinguishes beliefs about usefulness and ease of use from the behavior that those beliefs may help explain (Davis, 1989). The unified theory of technology acceptance similarly gives explicit roles to social and contextual conditions (Venkatesh et al., 2003). These approaches caution against equating a favorable opinion with regular or productive use. They also suggest that differences in educational opportunities can influence attitudes independently of personality.

The General Attitudes towards Artificial Intelligence Scale distinguishes positive and negative dimensions (Schepman & Rodway, 2020, 2023). Positive evaluations include perceived benefits and favorable reactions. Negative statements concern adverse consequences and reservations. The present reporting convention keeps these dimensions separate and uses the label AI concerns for endorsement of negative statements, with larger values indicating stronger concerns. This convention makes the substantive interpretation explicit and avoids obscuring ambivalence through a single favorable-attitude total.

Separating the dimensions permits students to recognize benefits while also identifying risks. Trust research shows that responses to AI depend on characteristics of the system, the task, and the interaction (Glikson & Woolley, 2020). Experimental evidence of algorithm aversion and algorithm appreciation likewise demonstrates that people's responses to algorithmic advice vary across circumstances (Dietvorst et al., 2015; Logg et al., 2019). Accordingly, a negative association between concerns and innovative self-perceptions should not be interpreted as evidence that concern is educationally undesirable.

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2.3 Human AI Learning and the Limits of Attitudinal Evidence

AI literacy frameworks emphasize understanding, use, evaluation, and ethical judgment (Long & Magerko, 2020; Ng et al., 2021). These capacities overlap only partly with positive attitudes. A student who understands model limitations may become more selective about when to use a system without becoming less capable of innovation. Conversely, enthusiasm can coexist with inaccurate expectations. Student accounts of generative AI include both perceived opportunities and concerns, reinforcing the importance of attending to these distinct orientations (Chan & Hu, 2023).

Experimental research provides a reason to study these distinctions without assuming a uniform benefit. Noy and Zhang (2023) found productivity benefits in incentivized professional writing tasks, while Doshi and Hauser (2024) reported gains in individual creative evaluations alongside reduced diversity across outputs. These findings concern performance under particular task conditions. They do not show that favorable AI attitudes cause enduring changes in personality or that every form of AI assistance improves independent learning.

The broader evidence also emphasizes contingency. Vaccaro et al. (2024) found that the benefits of combining people and AI depended on the comparison condition and task characteristics. Bastani et al. (2025) demonstrated that assistance during practice and learning demonstrated without assistance can diverge in mathematics. Cognitive offloading offers one explanation for why immediate task support and retained competence need separate evaluation (Risko & Gilbert, 2016). The present survey cannot adjudicate these mechanisms, but it can identify attitudinal associations that motivate more discriminating future designs.

2.4 Research Questions and Interpretive Boundaries

The conceptual model in Figure 1 treats the two AI-attitude dimensions as correlated statistical predictors of an innovative-personality score. Arrows indicate the direction in which the regression is written, not an established temporal process. Prior AI exposure, digital competence, educational opportunities, and general openness could contribute to both sides of the association.

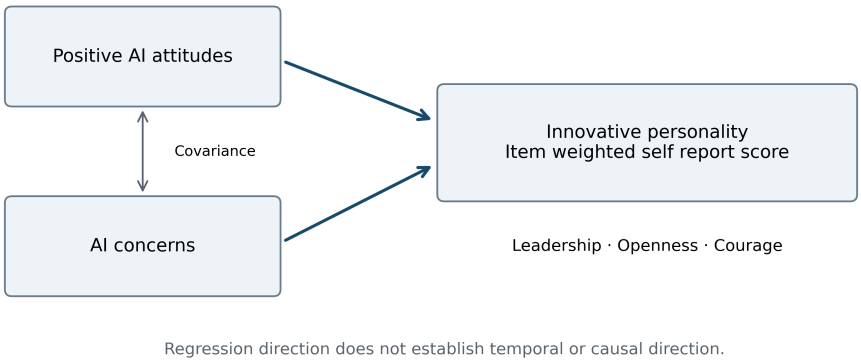

Fig. 1: Model of the concurrent associations

Note. Arrows indicate regression direction only. Positive attitudes and concerns remain separate. The three personality labels summarize the local adaptation.

The study addresses four questions. RQ1 asks how overall innovative personality is associated with positive AI attitudes and the negative-attitude score. RQ2 asks how much variance is jointly and uniquely associated with the two attitude dimensions. RQ3 asks whether overall personality and the two attitude scores differ by gender or academic field. RQ4 asks how students' personality scores are distributed relative to the response midpoint.

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3 Method

3.1 Design and Setting

The study used a cross-sectional questionnaire design at a university in Saudi Arabia. Electronic data collection extended over four months during the first and second semesters of academic year 1446 AH. The measures comprised a demographic form, an Arabic adaptation of the innovative-personality instrument, and an Arabic adaptation of the General Attitudes towards Artificial Intelligence Scale. The design did not manipulate AI exposure or assign participants to an instructional condition.

3.2 Participants and Sampling Scope

The main sample contained 438 students aged 18–24 years. Women represented 59.1% of participants and men 40.9%; 53.4% studied in scientific disciplines and 46.6% in humanities disciplines. An independent pilot sample of 100 students was used to examine the instruments before main data collection. Table 1 presents the main sample margins. Pilot participants are not included in the main analytic denominator.

Table 1: Participant characteristics

Characteristic	Category	*n*	%
Gender	Men	179	40.9
Gender	Women	259	59.1
Academic field	Scientific disciplines	234	53.4
Academic field	Humanities	204	46.6
Main sample	All participants	438	100.0

Note. Age range = 18–24 years. An independent pilot contained 100 students. Gender-by-field joint cell counts are not inferred from these margins.

Inference is directed to the participating students. Recruitment probabilities, participation rates, and population coverage determine whether a broader institutional inference is defensible; a sample count alone does not establish representativeness. The analysis therefore does not use population weights or extrapolate prevalence to the university's full enrollment. Gender and academic field are retained as the categories recorded in the study, without treating them as exhaustive descriptions of students' identities or educational experiences.

3.3 Measures and Score Construction

The demographic form recorded gender and academic field. It was a descriptive form rather than a psychometric scale. Actual AI-use frequency, specific application use, AI literacy, creative products, and academic attainment were not assessed as study outcomes. The AI measure consequently concerns general orientations toward AI applications, including applications beyond generative conversational systems.

The locally adapted innovative-personality questionnaire contained 19 items assigned to leadership, openness, and courage. Under the local item map, the dimensions contained 6, 6, and 7 items, respectively. Responses ranged from 1, strongly disagree, to 5, strongly agree. Dimension scores were item means; the overall score was the mean of all 19 items. Consequently, the composite weighted the dimensions by their item counts. Summed scores were calculated only as equivalent representations of these means, with possible ranges of 6–30, 6–30, 7–35, and 19–95.

The AI questionnaire contained 20 items, with 12 positive statements and 8 negative statements. The reporting specification used five response options scored from 1 to 5 and calculated a separate mean for each dimension. Positive items were scored so that larger values indicated more favorable evaluations. Negative items were retained in endorsement direction so that larger values indicated stronger AI concerns; they were not combined with positive items into a single score. Table 2 specifies the interpretive direction and denominator of each scale. A linear recoding changes means and coefficient signs in predictable ways, which makes the direction of scoring part of the substantive definition of the construct.

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Table 2: Measures and pilot consistency coefficients

Scale or dimension	Items	Direction of larger scores	Pilot α	Split half
Leadership	6	Stronger endorsement	.897	.844
Openness	6	Stronger endorsement	.700	.614
Courage	7	Stronger endorsement	.850	.839
Overall innovative personality	19	Stronger endorsement	.897	.844
Positive AI attitudes	12	More favorable evaluations	.800	.777
AI concerns	8	Stronger concern endorsement	.837	.774

Note. Local scoring specification: five response categories; item means; no combined AI total. Pilot N = 100; split-half coefficients use Spearman–Brown correction. All reliability entries require pilot-output confirmation. These are not main-sample reliability estimates.

3.4 Translation and Preliminary Measurement Evidence

The source study describes researcher translation, contextual adaptation, and review by ten psychology faculty members, with agreement ranging from 80% to 100%. These procedures address perceived relevance and clarity. They are not equivalent to a complete evaluation of cross-cultural measurement equivalence. The distinction is consistent with the International Test Commission's (2018) guidance on documenting translation, adaptation, and the intended interpretation of scores.

Pilot internal-consistency estimates are summarized in Table 2. Item–subscale correlations were also reported, but their interpretation depends on whether each item was excluded from the subscale total before calculating the correlation. Correlations with totals that contain the same item are partly mechanical and should not be presented as independent construct-validity evidence. Likewise, a strong correlation between a subscale and the total score does not by itself validate a higher-order factor.

The study interprets pilot coefficients as limited evidence about internal consistency in that sample. Coefficient alpha does not prove unidimensionality, and its assumptions need consideration before treating it as a reliability estimate (Dunn et al., 2014; McNeish, 2018). No claim of established latent mean equivalence across gender or academic fields is made. Measurement invariance would be relevant to a stronger interpretation of those comparisons (Putnick & Bornstein, 2016). The supplementary appendix specifies the item-level checks needed for such an extension.

3.5 Statistical Strategy

The primary association analyses used the overall innovative-personality score and the two AI-attitude scores. Pearson correlations were accompanied by Fisher-transformed 95% confidence intervals and two-sided tests with 436 degrees of freedom. The two principal correlation tests formed one multiplicity family. Holm's (1979) sequential procedure was used to control the familywise error rate.

A two-predictor ordinary least-squares model summarized the concurrent association of positive attitudes and AI concerns with innovative personality. Reporting included unstandardized coefficients, standardized coefficients, confidence intervals, the omnibus F statistic, adjusted R^2, residual standard deviation, and a partition of explained variance into unique and shared components. These components describe sample covariance, not psychological mechanisms. The model is intentionally parsimonious and contains no interaction or mediation term unsupported by the research design.

The demographic analysis comprised six principal comparisons: overall personality, positive attitudes, and AI concerns by gender and by academic field. Welch tests and confidence intervals for mean differences were used to accommodate unequal variances. Hedges' g supplied a standardized descriptive effect size based on the pooled within-group standard deviation. Holm adjustment was applied across the six comparisons as one exploratory family. Confidence intervals in the tables are pointwise intervals, not simultaneous intervals; the adjusted probabilities govern familywise decisions.

Scores were described in item-mean units before being converted to summed-score units. Comparison with the midpoint of 3 assessed departure from the response scale's neutral anchor. It was not a test against a population norm or a classification rule. Standardized distances from that midpoint were included as descriptive quantities. Statistical significance against a response anchor was not interpreted as evidence of educationally important creative achievement.

The main analyses used a common denominator of 438 students with complete composite scores. This specification applies to the reporting model and all derived intervals. At this sample size, the Fisher transformation gives an approximate 80% power threshold of —r— = .134 for an individual two-sided test at $\alpha = .05$. This calculation describes sensitivity under independent sampling, not an a priori justification or evidence that a null result establishes equivalence (Lakens, 2022).

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The source analysis used IBM SPSS Statistics version 27. The expanded reporting distinguishes calculations recoverable from sample summaries from procedures requiring item-level or case-level information. Distributional diagnostics, influential observations, robust regression standard errors, missing-data sensitivity, and cross-validated performance require the latter. They are not inferred from a significant F statistic or reported as having passed. This separation follows the broader emphasis on transparent quantitative reporting in Appelbaum et al. (2018).

4 Results

4.1 Score Distributions

Table 3 presents the common score metric. Overall innovative personality averaged 4.170, SD = 0.567, equivalent to a summed mean of 79.232, SD = 10.765, across 19 items. Leadership, openness, and courage item means were 3.980, 4.368, and 4.164, respectively. The weighted combination of their means equals the overall mean. Positive AI attitudes averaged 3.521, while AI concerns averaged 2.931 under the five-category reporting convention.

Table 3: Descriptive scores in common item mean units

Scale	Mean	SD	95% CI for mean
Leadership	3.980	0.596	[3.924, 4.036]
Openness	4.368	0.607	[4.311, 4.425]
Courage	4.164	0.740	[4.094, 4.233]
Overall personality	4.170	0.567	[4.117, 4.223]
Positive AI attitudes	3.521	0.368	[3.487, 3.556]
AI concerns	2.931	0.543	[2.880, 2.982]

Note. N = 438; theoretical item-mean range = 1–5. Confidence intervals describe mean estimates, not the range of individual scores.

Scores near the favorable end of the personality scale indicate strong self-endorsement. They do not establish an absence of ceiling effects: ceiling frequencies and item response distributions are separate quantities. The descriptive pattern is therefore interpreted as a feature of the questionnaire responses, without assuming normally distributed items or uniformly high levels of observable innovation.

4.2 Associations with Innovative Personality

The positive-attitude score correlated with overall innovative personality at r = .226, 95% CI [.135, .313]. The negative-attitude score correlated with personality at r = −.187, 95% CI [−.276, −.095]. Both associations remained below .001 after adjustment across the two primary tests. The coefficients correspond to 5.1% and 3.5% shared variance in separate bivariate relationships. These percentages overlap and should not be added to estimate the joint model's explanatory value.

Table 4: Overall personality correlations

AI score	r	95% CI	$t(436)$	Holm p
Positive attitudes	.226	[0.135, 0.313]	4.844	$< .001$
Negative attitude score	−.187	[−0.276, −0.095]	−3.975	$< .001$

Note. Reported source correlations; probabilities and Fisher intervals recalculated assuming 438 complete pairs. Holm adjustment covers two primary tests.

The pattern supports a modest association between innovative self-perceptions and favorable AI evaluations. Interpreting the inverse coefficient as an association with stronger concerns depends on retaining negative items in endorsement direction. Neither correlation demonstrates that students who use AI more frequently have more innovative personalities, because AI-use behavior was not measured. Nor do the correlations identify whether personality precedes attitudes, attitudes precede personality, or both reflect other characteristics.

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4.3 Concurrent Multivariable Association

The simultaneous model accounted for 6.2% of personality-score variance, adjusted $R^2 = .058$, $F(2, 435) = 14.376$, $p < .001$. The residual standard deviation was 0.550 item-mean units. Positive attitudes had an unstandardized coefficient of 0.277, 95% CI [0.123, 0.430], and a standardized coefficient of .180. AI concerns had an unstandardized coefficient of −0.119, 95% CI [−0.223, −0.015], and a standardized coefficient of −.114. Table 5 and Figure 2 present the coefficient estimates.

Table 5: Simultaneous regression for innovative personality

Predictor	*B*	SE	95% CI for *B*	*β*	*t*	*p*
Intercept	3.545	0.368	[2.822, 4.268]	—	9.642	< .001
Positive attitudes	0.277	0.078	[0.123, 0.430]	.180	3.541	< .001
AI concerns	−0.119	0.053	[−0.223, −0.015]	−.114	−2.251	.025

Note. N = 438; residual df = 435. $R^2 = .062$; adjusted $R^2 = .058$; $F(2, 435) = 14.376$, $p < .001$. Intervals and slope p values are pointwise.

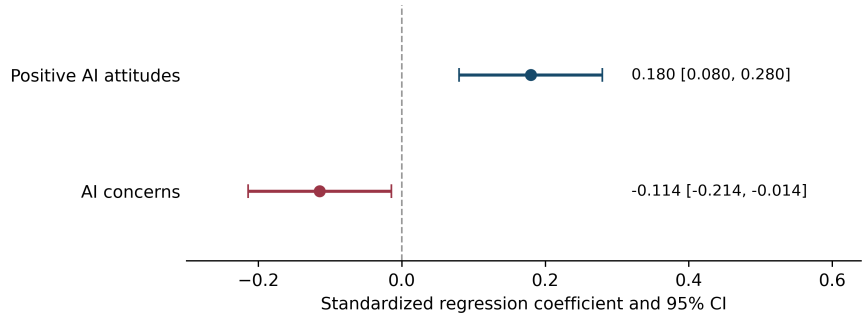

Fig. 2: Standardized coefficients with 95 percent intervals

Note. Both coefficients derive from the same two-predictor reporting model.

The positive-attitude coefficient represents the expected difference in personality score associated with a one-unit difference in favorable AI attitudes while holding the concern score constant. This is a conditional statistical contrast, not the expected result of changing an individual's attitude through an intervention. The same limitation applies to the negative coefficient. The intercept is a parameter of the fitted line and has no direct psychological interpretation because zero lies outside the predictor scales.

The variance partition assigned 2.70 percentage points to the unique contribution of positive attitudes, 1.09 points to the unique contribution of AI concerns, and 2.40 points to their shared contribution. The remaining 93.80% was not accounted for by the two predictors. The variance inflation factor was 1.196 for each predictor. This value describes their correlation in the model; it does not address omitted variables or measurement error. Table 6 presents the partition in percentage points to avoid confusing unique variance with standardized regression coefficients.

Table 6: Variance partition for the simultaneous model

Component	Percentage points of total variance
Positive attitudes unique	2.703
AI concerns unique	1.092
Shared contribution	2.405
Total accounted for	6.200
Not accounted for	93.800

Note. Unique components equal joint R^2 minus the other predictor's bivariate r^2. The components sum to 6.200 percentage points. These are covariance components, not causal mechanisms. applies to all entries.

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4.4 Gender and Academic Field Comparisons

The six principal contrasts are presented in Table 7 and Figure 3. Gender differences were small: the estimated men-minus-women differences were −0.024 for overall personality, −0.069 for positive attitudes, and −0.064 for AI concerns. Each confidence interval included zero. For positive attitudes, the Welch probability was .058; the corresponding equal-variance reference test was t(436) = −1.946, p = .052. Neither test supports a statistically significant gender difference at .05.

Table 7: Principal demographic contrasts

Contrast and outcome	Δ mean	95% CI	*g*	Welch *p*	Holm *p*
Gender · Overall personality	−0.024	[−0.134, 0.085]	−0.043	.662	1.000
Gender · Positive attitudes	−0.069	[−0.141, 0.002]	−0.189	.058	.292
Gender · AI concerns	−0.064	[−0.169, 0.040]	−0.118	.226	.906
Field · Overall personality	0.060	[−0.046, 0.167]	0.107	.265	.906
Field · Positive attitudes	0.090	[0.021, 0.159]	0.247	.010	.062
Field · AI concerns	−0.034	[−0.136, 0.069]	−0.062	.520	1.000

Note. Gender = men minus women; field = science minus humanities. N = 438. Intervals are pointwise; Holm p covers all six tests. Hedges' g uses the pooled within-group SD with small-sample correction.

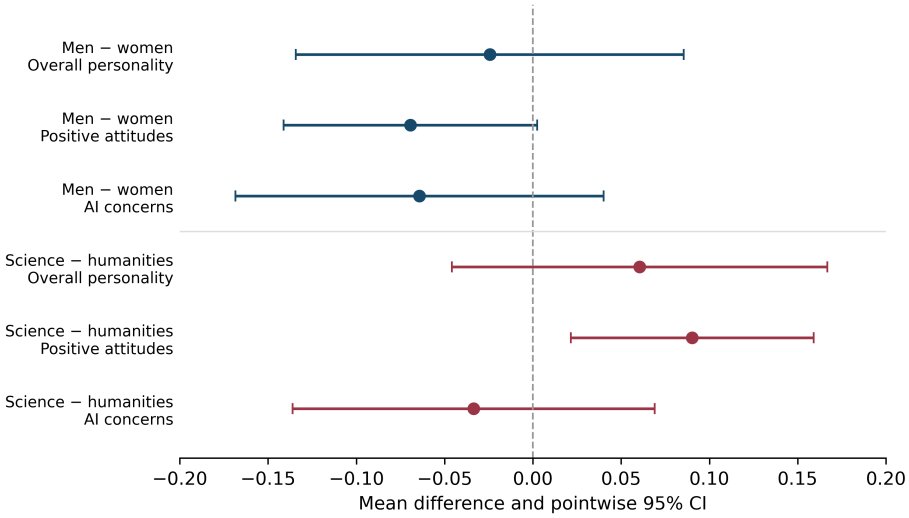

Fig. 3: Demographic contrasts with pointwise 95 percent intervals

Note. The vertical line denotes zero difference. Intervals are not adjusted for multiplicity; decisions use the six-test Holm adjustment in Table 7.

The science-minus-humanities difference in positive attitudes was 0.090, 95% CI [0.021, 0.159], g = 0.247, with an unadjusted p value of .010. After adjustment across the six comparisons, p = .062. This pattern is compatible with a modest field-related difference, but it does not meet the study's familywise decision rule. Overall personality and AI concerns did not show clear field contrasts. Nonsignificant results are not evidence of population equivalence, and the estimates remain conditional on comparable score interpretation across groups.

4.5 Endorsement Relative to the Response Midpoint

All personality means exceeded the midpoint of 3 in the reporting specification. For the overall score, the mean difference from the midpoint was 1.170 item-mean units, 95% CI [1.117, 1.223], t(437) = 43.222, p < .001. The same result

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expressed in summed units was 79.232 versus a midpoint of 57; both the mean difference and its standard error increased by the same factor of 19. Table 8 and Figure 4 display these equivalent representations and the dimension profiles.

Table 8: Equivalent summed scores and midpoint comparisons

Scale	Sum mean	Sum SD	Midpoint	$t(437)$	d_{midpoint}
Leadership	23.880	3.573	18	34.44	1.65
Openness	26.206	3.643	18	47.14	2.25
Courage	29.146	5.179	21	32.92	1.57
Overall personality	79.232	10.765	57	43.22	2.07

Note. All two-sided p values $< .001$. The standardized midpoint distance equals (item mean $-$ 3)/SD.

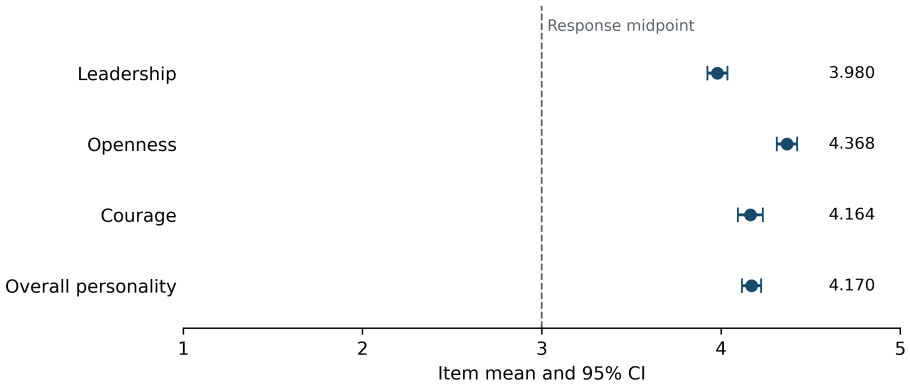

Fig. 4: Personality score profile on the full response scale

Note. The midpoint is a response anchor. Points represent mean endorsement, not prevalence or creative achievement.

This comparison concerns the center of a response scale. It does not estimate the proportion of innovative students, establish a clinical or educational cutoff, or show that the institution produces a particular level of creative achievement. The large standardized distance from the midpoint reflects the location and variability of self-reported responses; it should not be compared directly with effect sizes from interventions or group differences.

4.6 Sensitivity of Interpretation

Two sensitivities are particularly relevant. First, reversing the negative-attitude scale would reverse the signs of its bivariate and regression coefficients while leaving their absolute magnitudes, model fit, and probabilities unchanged. The label of that predictor must therefore identify whether the score represents concern or tolerance of AI's drawbacks. Second, an attenuation calculation using the pilot reliability range .777–.800 for positive attitudes and .897 for personality yields corrected positive correlations of approximately .276–.267. This narrow numerical range does not remove uncertainty about the appropriate reliability model or transfer pilot reliability to the main sample.

The substantive interpretation remains restrained: the associations are modest, the joint model leaves most score variance unexplained, and demographic comparisons do not establish robust group differences under the stated multiplicity rule. Sensitivity calculations are not substitutes for validation against item responses, independent creative outcomes, or future observations. The supplementary appendix documents the exact numerical dependencies and the analyses that require those further inputs.

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5 Discussion

5.1 Innovative Self Perceptions and AI Attitudes

The principal association pattern places favorable AI attitudes alongside higher self-reported innovative personality and the negative-attitude score alongside lower personality scores. The magnitudes are modest. Their confidence intervals exclude zero under the stated sample size, but this does not make the association a strong basis for individual decisions or for attributing innovation to technology. The pattern is consistent with a general exploratory orientation in which students who see themselves as receptive to new ideas also evaluate AI more favorably. It remains equally possible that prior experiences, educational resources, or other personality characteristics contribute to both measures.

This interpretation aligns with the distinction between dispositions and achievements in creativity research. Feist (1998) emphasizes personality in relation to domain-specific creative criteria, whereas Karwowski and Lebuda (2016) address creative self-beliefs. The present outcome belongs closer to the latter self-perceptual space than to a direct test of creative production. Associations between two self-report instruments may partly reflect shared self-presentation or response tendencies, which is one reason common-method processes deserve attention (Podsakoff et al., 2003).

The results also suggest that favorable AI attitudes and concerns should not be collapsed into a simple continuum of acceptance. A student can value AI's affordances and recognize its limitations simultaneously. Concern about unreliable information, privacy, or inappropriate delegation may support careful use. Interpreting caution as a deficit would move beyond both the instrument's scope and the evidence. The educationally relevant question is whether a student's evaluation is well calibrated to the task and system, not whether the student endorses AI without reservation.

5.2 Concurrent Explanation and Prospective Prediction

The model's 6.2% explained variance is meaningful as a description of covariance but insufficient as a claim of strong predictive performance. Model fit in the same observations used to estimate the coefficients can overstate how well the model will perform elsewhere. Shmueli (2010) distinguishes explanatory and predictive aims, while Yarkoni and Westfall (2017) emphasize evaluation beyond the estimation sample when prediction is the objective.

An application intended to identify innovative students would require an explicit target, performance criteria, validation data, and an assessment of consequences. The present results supply none of those conditions. They also do not justify screening students for innovation on the basis of AI attitudes. The small unique variance components indicate that large differences in personality scores remain among students with similar attitudes. Future research can test whether behavioral indicators of AI engagement add useful information after accounting for established personality and educational variables.

The covariance between the two attitude dimensions matters for the allocation of their coefficients. The same bivariate correlations can produce different conditional effects when predictor overlap changes. Consequently, the two coefficients should be interpreted together with the full correlation matrix and uncertainty estimates. The shared component in Table 6 is a statistical decomposition, not evidence that a common psychological process has been identified. A latent process would require an appropriate measurement model and a design capable of distinguishing competing explanations.

5.3 Demographic Contrasts and Educational Opportunity

The gender estimates do not support a clear difference under the stated tests. This should be expressed as an uncertainty-aware result, rather than as proof that gender can never matter or that the groups are psychologically identical. A small observed contrast can arise from sampling variation, limited measurement sensitivity, or genuinely similar experiences. Without a prespecified equivalence margin and an appropriate test, a nonsignificant comparison does not settle which explanation is correct.

The field contrast in positive attitudes is likewise tentative after familywise adjustment. Differences in curricular exposure, opportunities to use computational tools, or the perceived relevance of AI could contribute to this pattern. None of those mechanisms was directly measured, so explanations based on superior digital competence in one field remain proposals for future study. The result does not establish that science students are more innovative, and it does not justify treating humanities students as deficient in technology adoption.

For universities, an appropriate implication is to examine access and learning opportunities across fields. A common foundation in critical evaluation can coexist with discipline-specific activities: scientific courses may emphasize verification of numerical or analytical output, while humanities courses may examine interpretation, evidence, authorship, and the diversity of ideas. These are instructional possibilities grounded in the broader literature, not interventions evaluated by the present survey.

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5.4 Implications for Human AI Learning

The findings support studying the conditions under which exploratory attitudes translate into thoughtful use, but they do not establish that increasing positive attitudes will increase creativity. AI literacy offers a more discriminating educational objective. Understanding a tool's limitations, checking evidence, comparing alternatives, and deciding when assistance is appropriate connect favorable engagement to informed judgment (Long & Magerko, 2020; Ng et al., 2021). These capacities can be developed without requiring indiscriminate confidence in AI.

Instruction can also preserve opportunities for independent thinking. Buçinca et al. (2021) showed that cognitive forcing approaches can reduce overreliance in AI-assisted decision-making. In an educational setting, analogous activities could require an initial independent response, comparison with AI suggestions, and an explanation of the learner's final decision. The present study does not test such a sequence; it provides a reason to examine whether dispositions and attitudes predict engagement with it.

Creative learning requires attention to the output and the learner. Doshi and Hauser's (2024) distinction between individual quality and collective diversity suggests that an increase in average ratings can coexist with convergence across ideas. Bastani et al. (2025) further demonstrate the importance of performance when assistance is removed. A stronger evaluation of AI-supported innovation would therefore include independent transfer tasks and diversity-sensitive product judgments, alongside self-reports. These criteria would reveal whether students are developing capabilities that persist beyond the interaction.

5.5 Measurement and Contextual Limitations

The principal limitations concern construct interpretation, sampling, and design. The innovative-personality instrument was adapted from a teacher-oriented framework to university students, and the correspondence between item content and the intended constructs requires direct attention. Translation and expert review support clarity but do not establish structural validity. Main-sample factor analyses, item behavior, and reliability estimates would strengthen interpretation, especially if group comparisons remain a central aim.

The AI-attitude measure concerns general AI, whereas much recent educational discussion centers on generative AI. Participants may have different applications in mind when responding. A favorable score may therefore reflect perceived societal usefulness rather than frequent classroom use. Recording application, purpose, frequency, and verification behavior would help separate these possibilities in future studies.

Sampling at one institution limits generalization. The study's age range and gender and field composition define its immediate scope, but they do not address nonparticipation or differences across Saudi universities. Neither a population enrollment total nor a large sample can by itself correct an undocumented selection process. Future multisite work should retain institutional and course identifiers so that clustering and local opportunities can be examined directly.

Cross-sectional self-reports leave causal order unresolved and may share response biases. Additional variables should be chosen from a substantive causal model rather than added indiscriminately to a regression (Rohrer, 2018). Residual diagnostics, missingness analyses, and out-of-sample evaluation are necessary before extending the present model to robust estimation or prospective prediction. More elaborate statistics cannot compensate for unclear scoring, uncertain instrument provenance, or a mismatch between the research question and what was measured.

5.6 Directions for Future Research

A longitudinal extension could assess dispositions and attitudes before recording AI engagement, then evaluate creative products and independent performance after a defined period. The temporal separation would improve interpretation without by itself eliminating confounding. A complementary experiment could vary the form of assistance and require common tasks, blind ratings of originality and usefulness, and a subsequent task completed without AI. Both designs would retain the distinction between learning conditions and learning outcomes.

Measurement development should precede comparisons of latent means. The translated items, response anchors, scoring key, and adaptation decisions should be documented, with cognitive interviewing used prospectively to examine how students interpret them. Factor structure and invariance can then be evaluated with methods appropriate to ordinal responses. Qualitative interviews could explain patterns of critical use and ambivalence in a new mixed-method study; they should be treated as an additional data collection component, not inferred from the present questionnaires.

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6 Conclusion

Innovative personality and AI attitudes are related but distinct psychological constructs. In this Saudi university sample, the reported bivariate associations were modest, and the concurrent model linked the two attitude dimensions to a limited portion of personality-score variance. The demographic comparisons did not establish familywise-robust differences, and endorsement above a response midpoint did not establish the prevalence of innovative people. The most defensible contribution is an account of students' innovative self-perceptions and their attitudinal orientations toward AI. Claims about actual use, creative achievement, or durable learning require direct measurement and designs matched to those outcomes.

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