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SELF-LEADERSHIP AND PSYCHOLOGICAL STRESS AS PREDICTORS OF ATTITUDES TOWARD ARTIFICIAL INTELLIGENCE AMONG PAKISTANI COLLEGE STUDENTS: A MULTI-THEORETICAL EXAMINATION

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Abstract
Artificial intelligence is now embedded in routine higher education practice, yet comparatively little is known about the psychological characteristics of the students using it. The present study addressed this gap through four theoretical frameworks: Self-Leadership Theory, Social Cognitive Theory, the Transactional Model of Stress and Coping, and the Technology Acceptance Model. Two hundred twenty-three Pakistani college students completed the Abbreviated Self-Leadership Questionnaire, the General Attitudes toward Artificial Intelligence Scale, and the Stress subscale of the Depression Anxiety Stress Scales (DASS-21). Internal consistency was adequate for all scales (alphas .77 to .86). Self-leadership was positively associated with positive AI attitudes ($r = .20$, $p = .003$) but showed no association with negative attitudes. Stress correlated positively with positive attitudes ($r = .22$, $p = .001$) and negatively with negative attitudes ($r = -.35$, $p < .001$). In the regression models, both predictors remained significant for positive attitudes ($R^2 = .109$), whereas stress was the sole significant predictor of negative attitudes ($R^2 = .129$). Interpreted through a transactional appraisal framework, this pattern suggests that students under academic pressure may appraise AI as a coping resource rather than as a threat. Self-regulatory capacity and stress appraisal therefore appear to operate through distinct pathways, a distinction with implications for institutions seeking to support constructive student use of AI.

Introduction
Artificial intelligence has entered higher education rapidly and is now embedded in routine academic practice. Students use it for information retrieval, for drafting and revising written work, for navigating adaptive learning systems, and for obtaining immediate feedback that would previously have required tutor availability. A question once largely theoretical has therefore become practical: why do some students regard AI as a resource, others with marked caution, and most somewhere in between? Exposure alone

provides an insufficient explanation, since students with comparable access diverge substantially. A more plausible account is that such attitudes rest on psychological dispositions established well before initial contact with AI tools (Schepman and Rodway 2020; Stein et al. 2024).

We focus on two such processes. Self-leadership covers the cognitive and behavioral strategies individuals use to direct their own cognition and behavior toward self-endorsed goals. Psychological stress refers to the subjective experience of demands exceeding one's perceived capacity to manage them. Each has a long research tradition behind it. Each also has an evident, though largely untested, bearing on how individuals appraise a technology as unfamiliar as AI. Rather than examining them separately, we model them jointly and address why they should relate to AI attitudes rather than only whether they do. Four theoretical frameworks organize this argument and are considered in turn below.

Literature Review

Self-Leadership Theory

Self-leadership was formalized by Manz (1986) and extended two decades later by Neck and Houghton (2006). It describes the processes through which individuals influence and direct themselves in the absence of external direction. The construct has three strategy families. Behavior-focused strategies include self-goal setting, self-observation, and self-reward. Natural reward strategies involve restructuring a task so that some element of it becomes intrinsically rewarding. Constructive thought pattern strategies cover self-talk and mental imagery. Surveying twenty years of work on the construct, Neck and Houghton (2006) reported that more frequent users of these strategies tend to exhibit higher self-efficacy, more positive affect, and better performance at work and in school.

No one has tested self-leadership against AI attitudes directly. The theory nonetheless generates a reasonably clear expectation. Learning an unfamiliar tool demands precisely the self-directed work the theory describes: determining what the tool is for, persisting with an unfamiliar interface long enough to attain competence, and regulating the frustration that accompanies this process. Students who already possess these habits are equipped for the task, whereas those who do not must improvise. On this reading, self-leadership should bear little on a student's assessment of the potential costs of AI. Its effect should instead fall on confidence during acquisition, which would be expected to manifest as positive, engagement-oriented attitudes rather than as attitudes grounded in fear or distrust.

Social Cognitive Theory and Self-Regulation

Bandura's (1991) social cognitive account of self-regulation offers a complementary reading, placing self-leadership-type processes inside a wider model of human agency. For Bandura, human functioning arises from continuous reciprocal interaction among personal factors, behavior, and environment, a relationship he termed triadic reciprocal causation. Self-efficacy anchors the model: what a person believes about their own capacity to organize and carry out what a given outcome demands. Self-regulation then runs through three sub-processes, namely self-observation, judgment of performance against personal or social standards, and affective self-reaction. Together these enable individuals to adjust their course without relying on external evaluation.

What Social Cognitive Theory adds is an answer to a question the self-leadership account leaves unresolved: why should self-directed strategies carry over into a domain the person has never encountered? Efficacy beliefs do transfer, at least partly, across tasks that make comparable demands, such as sustained attention, tolerance for failing early on, and building a skill piece by piece. A student with well-established self-regulatory habits in coursework should transfer some of that confidence to AI-assisted work. The theory thus links the relatively stable quality usually attributed to self-leadership with a domain

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that did not exist when most of those habits were formed.

The Transactional Model of Stress and Coping

For stress, the most directly applicable framework is that of Lazarus and Folkman (1984). Their central claim is that stress does not reside in the event itself. It is produced by a cognitive appraisal that ties person to environment. Primary appraisal sorts a situation into irrelevant, benign, or stressful, and if stressful, asks whether the harm is already done, still coming, or whether the situation is instead a challenge carrying the possibility of mastery. Secondary appraisal evaluates the coping resources available. One consequence is that an identical stimulus, here the arrival of unfamiliar AI in a student's academic environment, can be read very differently by two people, depending on the demands and resources each brings to it.

This yields a falsifiable prediction that runs counter to intuition. The intuitive expectation is that stressed students would be more wary of unfamiliar technology rather than less so. If, however, a stressed student appraises AI as a coping resource, that is, as a means of narrowing the gap between demands and perceived capacity, then stress should covary positively with positive AI attitudes and negatively with distrust-based negative attitudes. This is the pattern observed here, as reported below. A straightforward threat account of stress cannot generate it.

The Technology Acceptance Model

Davis (1989) built the Technology Acceptance Model to explain why people take up a technology or refuse it, and it remains among the most widely applied models in that literature. TAM locates intention to use in two beliefs: perceived usefulness, meaning whether the person expects a performance gain, and perceived ease of use, meaning whether they expect to manage the tool without undue effort. Neither construct was measured as a discrete variable in the present study. TAM is nonetheless retained here because it connects the other three frameworks to the outcome we did measure, general attitudes toward AI. The two predictors may reach that outcome by partly different pathways. A self-directed student, better able to manage an unfamiliar interface, plausibly perceives the tool as easier to use. A stressed student who treats AI as a coping resource is, by definition, appraising it as useful. We return to this dual-pathway proposition in the Discussion, where findings are available against which to evaluate it.

Present Study

These frameworks point to two aims. The first was to determine whether self-leadership, understood as a reasonably stable individual difference in self-regulatory capacity, is associated with AI attitudes among Pakistani college students; Self-Leadership Theory and Social Cognitive Theory both predict a positive association with positive attitudes. The second concerned psychological stress, which we left as an open empirical question rather than a directional hypothesis, since the Transactional Model tolerates either sign depending on how AI is appraised. Pakistan constitutes a well-suited context for these questions. AI adoption in its higher education sector is still early, and a large, rapidly growing student population is encountering these tools under considerable academic and economic pressure. Appraisal processes should therefore be unusually salient under these conditions (Abbas et al. 2024; Barra et al. 2024).

Hypotheses

H1: Higher self-leadership will be positively associated with positive attitudes toward AI.

H2: Self-leadership will show no substantive association with negative attitudes toward AI, because we expect self-regulatory capacity to shape a student's confidence in their own engagement rather than their judgments about what technology may cost more broadly.

H3: Psychological stress will be associated with attitudes toward AI. We treat the direction of that

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association as an open question, since the Transactional Model of Stress and Coping permits AI to be appraised either as a threat or as a coping resource.

H4: Entered simultaneously with age, gender, and year of study as covariates, self-leadership and psychological stress will jointly predict positive attitudes toward AI.

Methodology

Research Design

The study was quantitative, cross-sectional, and correlational. It examined how self-leadership and psychological stress relate to attitudes toward artificial intelligence in a college student sample.

Participants

Participants were 223 college students drawn from public and private institutions in Pakistan. The sample was predominantly female: 190 women (85.2%) and 33 men (14.8%). Ages ran from 15 to 50 (M = 23.82, SD = 5.90). Fifty-seven were first-year students (25.6%), 111 were in their third year (49.8%), and 55 were in their fourth (24.7%). Two hundred lived in urban settings (89.7%), and the remaining 23 lived in rural areas (10.3%).

Inclusion and Exclusion Criteria

Recruitment was purposive and required at least some prior familiarity with, or exposure to, AI-based educational tools. This ensured that every respondent had a basis for holding an attitude toward the technology under study. All participants were in good physical and mental health and were able to give independent, informed consent for the duration of the study.

Procedure

The survey was self-administered and distributed online through Google Forms. Participation was voluntary and uncompensated, and completion took roughly 25 to 30 minutes.

Ethical Considerations

Participant risk did not exceed that of ordinary academic activity. Participation was voluntary, responses were anonymous, and a participant could withdraw at any point up to submission. Formal approval and consent details are given in the declarations at the end of the article.

Measures

Abbreviated Self-Leadership Questionnaire (ASLQ). Self-leadership was measured with the 9-item ASLQ (Houghton et al. 2012), rated 1 (Strongly Disagree) to 5 (Strongly Agree), with no reverse-scored items. We averaged across items, so higher scores mean more frequent use of self-leadership strategies. Alphas reported in earlier work run from .74 to .87 (Houghton et al. 2012).

General Attitudes toward Artificial Intelligence Scale (GAAIS). AI attitudes were measured with the 20-item GAAIS (Schepman and Rodway 2020), which contains a 12-item Positive Attitudes subscale and an 8-item reverse-scored Negative Attitudes subscale. Following the developers, we analyzed the subscales separately rather than combining them, scoring each as the mean of its items (possible range 1.00 to 5.00).

Depression Anxiety Stress Scales (DASS-21), Stress subscale. Stress was measured with the seven-item DASS-21 Stress subscale (Lovibond and Lovibond 1995), rated for the previous week from 0 (Did not apply to me at all) to 3 (Applied to me very much or most of the time), then summed and doubled per the standard scoring convention. During data preparation, we observed that the raw stored values for these items exceeded the labeled 0–3 range: four items ran 1 to 4 and three ran 1 to 5. After consulting the researcher who originally collected the data, we recoded each item as the raw value capped at 3. The resulting observed Stress range in this sample was 14 to 42.

Data Analytic Strategy

We ran the analyses in IBM SPSS Statistics (Version 27) and, as a verification check, independently re-derived every scored variable in a

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parallel formula-driven Excel workbook. We computed descriptive statistics and Cronbach's alpha for all scales, then Pearson correlations, and finally multiple linear regressions with Self-Leadership and Stress entered simultaneously as predictors of GAAIS Positive and GAAIS Negative attitudes, controlling for age, gender, and year of study. Alpha was set at .05 throughout. All regression coefficients reported here are unstandardized.

Results

Sample Characteristics

Table 1 Demographic Characteristics of the Sample (N = 223)

Characteristic	*n*	%
Gender		
Female	190	85.2
Male	33	14.8
Year of study		
First year	57	25.6
Third year	111	49.8
Fourth year	55	24.7
Residence		
Urban	200	89.7
Rural	23	10.3

Note. *N* = 223. Age: M = 23.82, SD = 5.90, range 15–50 years. Percentages may not total 100 due to rounding.

Descriptive Statistics

Table 2 Descriptive Statistics for Study Variables (N = 223)

Variable	*N*	*M*	*SD*	Min	Max	Skewness	Kurtosis
Age	223	23.82	5.90	15.00	50.00	2.12	4.43
Self-Leadership	223	3.39	0.68	1.67	5.00	0.05	-0.40
GAAIS Positive	223	3.16	0.71	1.00	4.58	-0.70	0.82
GAAIS Negative	223	2.86	0.75	1.38	5.00	0.63	0.70
DASS-21 Stress	223	29.84	7.72	14.00	42.00	-0.41	-0.65

Note. *M* = mean; *SD* = standard deviation. Self-Leadership and GAAIS subscales are scored on a 1–5 metric; DASS-21 Stress is scored 14–42 following the corrected item recoding described in the Methodology.

Table 2 presents descriptive statistics for the four study variables. Distributions approximated normality with the exception of Age, which was positively skewed (skew = 2.12), reflecting the concentration of respondents within the typical undergraduate age range.

Reliability of Measures

Table 3 Internal Consistency Reliability of Study Measures

Scale	*k*	α
Self-Leadership (ASLQ total)	9	.765
GAAIS Positive Attitudes	12	.856

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GAAIS Negative Attitudes	8	.807
DASS-21 Stress (corrected)	7	.819

Note. *k* = number of items. α = Cronbach's alpha. Interpretation bands: ≥ .90 excellent, ≥ .80 good, ≥ .70 acceptable, ≥ .60 questionable, ≥ .50 poor, < .50 unacceptable.
Internal consistency was acceptable to good across all four scales (α = .765 to .856).

Correlation Analysis

Table 4 Pearson Correlations Among Study Variables

Variable	1	2	3	4
1. Self-Leadership	—			
2. GAAIS Positive	.20**	—		
3. GAAIS Negative	.00	-.57**	—	
4. DASS-21 Stress	-.07	.22**	-.35**	—

Note. ***p* < .01.

Pearson correlations appear in Table 4. Self-Leadership was related to GAAIS Positive attitudes only ($r = .20$, $p = .003$). Stress was positively related to Positive attitudes ($r = .22$, $p = .001$) and negatively related to Negative attitudes ($r = -.35$, $p < .001$).

Regression Analysis

Table 5 Multiple Regression of Self-Leadership and Stress on GAAIS Positive and Negative Attitudes

Outcome: GAAIS Positive Attitudes ($R^2 = .109$, $F(5, 217) = 5.32$, $p < .001$)

Predictor	*B*	*SE*	*t*	*p*
Self-Leadership	0.217	0.068	3.20	.002**
DASS-21 Stress	0.022	0.006	3.65	< .001**
Age	0.011	0.008	1.43	.155
Gender	0.140	0.131	1.07	.286
Year of Study	-0.020	0.042	-0.48	.633

Outcome: GAAIS Negative Attitudes ($R^2 = .129$, $F(5, 217) = 6.40$, $p < .001$)

Predictor	*B*	*SE*	*t*	*p*
Self-Leadership	-0.021	0.071	-0.30	.767
DASS-21 Stress	-0.035	0.006	-5.60	< .001**
Age	-0.005	0.008	-0.62	.538
Gender	-0.043	0.137	-0.31	.754

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Year of Study	-0.010	0.044	-0.23	.821

Note. B = unstandardized regression coefficient. Gender coded 1 = Male, 2 = Female. ***p* < .01.

Table 5 presents both regression models. Self-Leadership and Stress together predicted GAAIS Positive attitudes ($R^2 = .109$, $p < .001$). For GAAIS Negative attitudes, Stress was the only predictor to reach significance ($R^2 = .129$, $p < .001$).

Set against the hypotheses, H1 held: self-leadership was positively related to positive AI attitudes. No association emerged for negative attitudes, which is consistent with H2, though a null result is weak evidence and we claim no more than consistency. H3 was posed as an open question and resolved toward a resource appraisal, with stress covarying positively with positive attitudes and negatively with negative ones. H4 held as well, since both predictors were significant for positive attitudes once age, gender, and year of study were in the model.

Discussion

Self-Leadership, Self-Regulation, and Engagement with AI

The central prediction drawn from Self-Leadership Theory and Social Cognitive Theory was supported. Students who reported using self-leadership strategies more often also reported more favorable attitudes toward AI, and the association survived controls for stress, age, gender, and year of study. This is consistent with Neck and Houghton's (2006) treatment of self-leadership as a general-purpose resource people carry into novel and demanding tasks, and with Bandura's (1991) argument that self-regulatory capacity developed in one domain transfers, at least partially, to others. A student accustomed to setting goals, monitoring their own progress, and managing the affective disruption that accompanies early failure appears better positioned to approach AI with curiosity rather than avoidance.

The specificity of this pattern warrants attention. Self-leadership related to positive AI attitudes and showed no detectable association with negative ones, in the correlations and in the regression alike. That asymmetry suggests self-leadership operates on the approach side of a student's relationship with AI, namely the interest and willingness to engage that the GAAIS Positive subscale captures, while leaving the fear, distrust, and ethical concern indexed by the Negative subscale largely unaffected. In Social Cognitive Theory terms, self-efficacy may raise a student's confidence in their own ability to use AI well without shifting what they believe about its risks to privacy, academic integrity, or human judgment. If so, the two evaluative streams draw on different psychological resources, and self-leadership speaks only to the first.

Stress as Appraisal: A Transactional Interpretation

The stress result is the most theoretically consequential finding of the study and requires the most careful interpretation. The intuitive expectation is that a student already under strain would respond defensively to further uncertainty, such that more stressed students would be more apprehensive about AI. The data indicate otherwise. Stress correlated positively with positive AI attitudes and negatively with negative ones, produced the largest t statistic in both regression models, and was the only significant predictor of negative attitudes.

The Transactional Model of Stress and Coping (Lazarus and Folkman 1984) accommodates this result without difficulty. Stress there is the output of an appraisal, not a property of the stimulus, so the same stimulus may be registered as threat, as loss, or as challenge depending on the resources and demands the perceiver brings to it. One plausible reading of our result is that by the time students under heavy academic pressure meet AI tools, they are already appraising them through a

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resource lens rather than a threat lens. AI is perceived as a means of narrowing the distance between task demands and the time available to meet them rather than as an additional burden on an already loaded system. Under that appraisal AI becomes what Lazarus and Folkman would call a coping resource, and the attitudinal signature should be exactly what we observed: a positive orientation toward it, together with reduced distrust.

A more conservative interpretation is equally available, and a cross-sectional correlational design cannot exclude it. Something else (general academic engagement, course load, or exposure to AI-saturated coursework) could raise reported stress and AI attitudes independently. The direction of influence may also be reversed. Students already well disposed toward AI may rely on it more heavily as a coping tool, and heavy use might itself inflate self-reported stress if it brings dependency or academic-integrity worries that the GAAIS does not register. Our data cannot separate appraisal-driven reinterpretation from third-variable confounding or from reverse causation. Longitudinal designs are the appropriate remedy.

Integrating the Technology Acceptance Model

The Technology Acceptance Model (Davis 1989) provides a useful frame for both sets of findings, even though we did not measure perceived usefulness or ease of use directly. Self-leadership may raise positive attitudes by way of perceived ease of use, since a student practiced at self-directed learning likely encounters less difficulty on first contact with an AI tool. Stress, under the resource-appraisal reading, would work instead through perceived usefulness, because a stressed student may rate the same tool as more useful precisely when the need for support is sharpest. If the dual-pathway account is correct, the two predictors reach a single global measure by partly different routes, which would also help explain why they were essentially unrelated to each other in this sample ($r = -.07$, $p = .308$).

Practical Implications

These findings carry practical implications for institutions seeking to encourage constructive AI adoption among Pakistani college students. The sample's mean GAAIS Positive score fell in the Neutral band, and its mean GAAIS Negative score sat at the upper edge of the Negative band (Schepman and Rodway 2020). This describes a student body still forming its position rather than one settled into either enthusiasm or rejection. Given that self-leadership showed a modest but theoretically coherent association with favorable attitudes, institutions may achieve greater effect by cultivating general self-regulatory skills (goal-setting, self-monitoring, constructive self-talk) than from technology-specific messaging about AI alone. Self-leadership strategies have the further advantage of being trainable (Neck and Houghton 2006), which makes them a viable intervention target rather than a fixed trait to be accommodated.

The stress finding points in a different direction and warrants greater caution. If elevated stress really is pushing some students to appraise AI as a coping resource, the appraisal may appear adaptive without being sustainable. Reliance on AI to manage stress carries risks of its own, including over-reliance and reduced engagement with foundational skill-building, neither of which a general attitude measure would capture. The present data cannot resolve this question. It nonetheless warrants consideration before positive AI attitudes among highly stressed students are interpreted as an unambiguously favorable outcome.

Limitations

Several limitations qualify these conclusions. Sampling was purposive, and the sample was heavily skewed toward female (85.2%) and urban (89.7%), which limits generalization to Pakistani college students at large and may affect the size, though probably not the sign, of the associations we report. The cross-sectional design precludes causal claims; the data are approximately equally consistent with self-leadership and stress influencing AI attitudes, with AI attitudes influencing self-reported stress, and with reciprocal influence over time. All three constructs were self-reported, so shared-method variance may contribute to the observed associations, including the strong negative correlation between the two GAAIS subscales. The DASS-21 Stress items also required a recoding correction after a discrepancy emerged between the SPSS value labels and the raw stored values. We made that correction transparently and in consultation with the researcher who originally collected the data, but it left the Stress range restricted (14–42 rather than the standard 0–42), which should be borne in mind when comparing this sample with studies using the unmodified item scale. Since our coefficients are unstandardized and Self-Leadership and Stress sit on different metrics, their magnitudes should not be read against each other; standardized coefficients would be required for that. Finally, we did not measure perceived usefulness or perceived ease of use, so their role above is interpretive rather than empirically tested.

Future Directions

Several extensions would advance this line of work. Following the same students across a semester of growing AI exposure would permit the stress-attitude relationship to be examined for direction and stability, and would permit a more direct test of the appraisal mechanism, for instance by checking whether appraising AI as threat versus resource mediates the path from stress to attitude. Adding direct measures of perceived usefulness and ease of use alongside the GAAIS would render the dual-pathway account empirically testable rather than post hoc. Manipulating self-leadership experimentally, through a short skills-training intervention, would provide a firmer causal test. Given the pronounced urban and female skew of the present sample, subsequent studies should pursue more demographically balanced sampling, to establish whether these patterns, and the stress finding in particular, hold across gender, residence type, and socioeconomic strata.

Conclusion

We asked how self-leadership and psychological stress relate to attitudes toward artificial intelligence among Pakistani college students. Self-leadership related to positive attitudes specifically, which is the pattern expected if self-regulatory capacity underwrites confident engagement with unfamiliar technology. Stress related to both positive and negative attitudes, in a pattern that a simple threat account cannot produce. Interpreted cautiously, as a cross-sectional design requires, that pattern is consistent with a transactional appraisal process in which stressed students come to perceive AI as a source of support rather than as an additional burden. Taken together, the findings identify self-regulatory capacity and stress appraisal as theoretically grounded and potentially actionable factors in how students form views about AI, and they delineate the longitudinal and experimental work required to test the causal claims that can only be raised here.

Use of AI and AI-Assisted Technologies

AI tools were used to assist with language editing, organization, and refinement of this manuscript, and with drafting portions of the hypotheses and the declarations sections. The authors reviewed all such material, verified the accuracy of the data, statistics, and citations, and take full responsibility for the final content and conclusions of the article.

Author Contributions

Aoun Ali: conceptualization, methodology, formal analysis, and writing. Sharjeel Ahmed: literature review, data curation, and review and editing. Syed Hussain Ali Shah Jillani: proofreading. All authors approved the final manuscript.

Conflicts of Interest

The authors declare no conflicts of interest with respect to the authorship or publication of this article.

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Ethical Approval and Informed Consent
Ethical approval for this study was granted by the institutional ethical committee of Government College of Education Federal B Area, Karachi, prior to data collection. Informed consent was obtained from all individual participants included in the study.

Data Availability
The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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