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AI Exposure and Career Anxiety amongst Indian College Students

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Abstract
As Artificial Intelligence (AI) technologies rapidly develop and are deployed, Indian students increasingly need to understand and learn AI-related skills for future employment. This study examines the effect of AI exposure and Career Anxiety on Indian College students. Using a quantitative approach, data were collected through an online survey facilitated by Google Forms, asking 30 Indian college-going students about their opinions on certain AI scales. All valid responses were analysed through Partial Least Squares Structural Equation Modelling (PLS-SEM). The results show that AI exposure, Career Anxiety and various other parameters like Career Self-Efficacy and Job Seeking Anxiety have a paradigm effect on the careers of Indian students. The study contributes to the literature by highlighting the adaptive role of Career Anxiety in transforming AI-related fear into proactive upskilling intention among undergraduate students and offers practical implications for higher education institutions and policymakers in responding to AI-driven labour market change.

Keywords: AI Exposure, Career Anxiety, Job Seeking Anxiety, Career Self-efficacy

1. Introduction

The rapid advancement in technology and innovation has made Artificial Intelligence an integral part of our lives. A survey of Indian white-collar workers revealed that 55% had adopted AI tools, 48% were receiving training, but 68% feared that their jobs could be automated within 5 years (Chakrabarti et al., 2024). Taking this into consideration, it is pivotal to navigate through the implications, effects and various elements that AI has introduced in our lives. Moreover, given the current scenario for students, the growth of AI means that millions of traditional jobs could be replaced globally, directly affecting the educational requirements needed to set students up for success. AI and data have the potential to add nearly \$450-500 billion to India's economy by 2025. Existing literature predominantly focuses on the economic projections of AI or the technical curricula required. There is a lack of comprehensive research addressing the structural barriers in higher education—such as faculty readiness and ongoing skills mismatches—and how these factors translate into psychological impacts like career anxiety among Indian students. Furthermore, the Indian research demographics lack proper, solid and dependable data discerning the true effects of AI exposure and career anxiety amongst Indian students. Emerging evidence suggests AI anxiety may alter career-related attitudes by modifying perceptions of social expectation, peer influences, and self-perceived competence, thereby affecting their career decisions. To make our investigation relevant and successful, we shall understand certain basic variables like Career Self-Efficacy (CSE), Job Seeking Anxiety (JSA), Career Anxiety (CA), and other terms like AI exposure and literacy. In particular, AI exposure refers to a metric that estimates the extent to which a job, task, or industry relies on or could be impacted by artificial intelligence. The accelerated development of AI technologies has amplified cognitive uncertainty regarding future careers among college students, positioning AI anxiety and exposure as critical factors influencing career decisions. Thus, the purpose of this study is to investigate the impact of AI exposure on the career and job-seeking anxiety of university students in India. By examining the mediating roles of career self-efficacy and AI literacy, this research aims to understand how students navigate the uncertainties of an AI-disrupted labour market.

Research Questions and Hypotheses

The meteoric ascendancy of artificial intelligence has reconfigured the global employment landscape, engendering widespread apprehension among college students regarding their professional trajectories and career viability (Duan et al., 2026). Against this backdrop, the present study develops four research questions, each of which corresponds to exactly one hypothesis so that the conceptual model and the empirical tests remain in direct alignment.

1. Is AI exposure associated with career anxiety among Indian college-going students? (tested by H4)
2. Is AI exposure associated with job-seeking anxiety among Indian college-going students? (tested by H2)
3. Does career self-efficacy mediate the relationship between AI exposure and career anxiety? (tested by H1)
4. Does AI literacy mediate the relationship between AI exposure and career anxiety? (tested by H3)

Research questions one and two address the direct associations in the model; research questions three and four address the two proposed indirect pathways. The hypothesis labels H1 to H4 are retained from the original conceptual model presented in Figure 1 so that the figure, the hypotheses and the results tables remain consistent with one another. The theoretical rationale for each hypothesis is developed in the sections that follow, and each hypothesis is stated at the point where its rationale has been fully established.

Theoretical Framework

This study is anchored in three complementary theoretical positions, which together specify why AI exposure should be expected to translate into career-related anxiety, and why that translation should operate through psychological rather than purely technical resources.

Social Cognitive Career Theory as the organising framework

Social Cognitive Career Theory (Lent et al., 1994) holds that career interest, choice and persistence are governed by three cognitive variables: self-efficacy beliefs, outcome expectations, and personal goals. Critically for the present study, SCCT does not treat these variables as arising in a vacuum. It specifies that contextual affordances and barriers — features of the environment that a person perceives as helping or hindering their progress — feed directly into self-efficacy and outcome expectations. Perceived AI exposure is theorised here as precisely such a contextual barrier. A student who perceives that smart technology and automation could perform the tasks associated with their intended occupation is encountering an environmental condition that undermines the belief that effort in that occupational direction will yield the expected return. SCCT therefore supplies the overall architecture of the model: an environmental barrier (AI exposure) acts upon a cognitive resource (career self-efficacy), which in turn shapes an affective career outcome (career anxiety).

Self-efficacy theory as the mechanism

Within that architecture, Bandura's (1977) self-efficacy theory specifies the mechanism. Self-efficacy is the belief in one's capability to organise and execute the actions required to produce given attainments, and Bandura identified physiological and affective states as one of its four sources. Perceived technological threat operates on exactly this source: awareness that one's intended field may be automated raises arousal and simultaneously devalues the mastery experiences a student has accumulated, since those experiences were acquired in a domain now perceived as unstable. The prediction that follows is directional and specific — AI exposure should depress career self-efficacy, and depressed career self-efficacy should elevate career anxiety.

Cognitive appraisal as the account of individual difference

Neither of the above explains why two students with comparable AI exposure report markedly different anxiety. Lazarus and Folkman's (1984) transactional model supplies that account. Stress arises not from an objective stimulus but from a two-stage appraisal: whether the situation is judged threatening (primary appraisal), and whether the individual judges their resources sufficient to cope (secondary appraisal). This framing generates the study's most theoretically interesting prediction. If AI literacy functions as a coping resource, it should attenuate the exposure–anxiety relationship at the secondary appraisal stage. If, however, greater literacy also sharpens a student's perception of what AI systems can actually displace, then literacy may raise threat appraisal at the same time as it raises coping appraisal, and the two effects may offset one another. The transactional model thus accommodates both a protective and a null result for AI literacy, and it is the framework against which the H3 finding is interpreted in the Discussion.

Taken together, these three positions specify the conceptual chain tested in this study: AI exposure functions as a perceived contextual barrier, which is appraised as a threat to future employability, which erodes career self-efficacy, which in turn elevates career anxiety and job-seeking anxiety. AI literacy is positioned as a candidate coping resource within this chain.

Conceptual Background and Hypothesis Development

The literature relating AI to career-related distress has converged on a small number of robust findings, but it also contains genuine inconsistencies that shape the hypotheses tested here. Across national contexts and disciplinary samples, the direct association between AI-related concern and career or employment anxiety has been replicated consistently. Dağ et al. (2026) found a positive and significant relationship in a sample of 821 Turkish health sciences students, with AI anxiety continuing to predict job-search anxiety after socio-demographic controls were entered. Duan et al. (2026) reported a comparable pattern among Chinese college students, and Rizkina et al. (2025), synthesising 32 studies published between 2020 and 2025, concluded that AI use is associated with heightened perceptions of job insecurity across workplace samples. The direct relationship, in short, is not in dispute.

Where the literature diverges is on what mitigates that relationship. One body of work treats technical knowledge as protective. Li et al. (2025), analysing 455 Chinese students, found that AI attitudes and AI literacy both carried significant mediating effects in the pathway from career self-efficacy to job-seeking anxiety, and Dağ et al. (2026) concluded their study by recommending AI literacy programmes as a remedy for job-search anxiety. A second body of work is less sanguine. Wang and Wang (2022) demonstrated that AI anxiety is not a unitary construct: learning anxiety and job replacement anxiety behaved differently in relation to motivated learning behaviour, with the latter functioning in a partly facilitative manner. Yaşar and Karagucuk (2025) similarly found AI anxiety to be associated with career indecision rather than uniformly with distress. These divergent findings suggest that the relationship between knowing about AI and feeling secure about one's career is not straightforwardly linear, and that a student who understands AI systems well may also understand more precisely which occupational tasks those systems can absorb.

Two further limitations characterise this literature and motivate the present study. First, the evidence base is geographically concentrated: the studies above are drawn from Chinese, Turkish and Taiwanese samples, and no comparable primary study has been conducted with Indian college-going students despite India's distinctive labour-market exposure profile. Second, most existing studies test AI literacy as a mediator situated between self-efficacy and anxiety, rather than examining whether literacy intervenes in the pathway running from exposure itself to anxiety. The present study addresses both gaps.

Career Self-Efficacy

Career self-efficacy is the belief in one's own ability to successfully navigate career-related tasks, including making decisions, pursuing a chosen field, and overcoming obstacles. Its role in the present model is that of a mediator, and the mediation claim requires two separate arguments to be established rather than one.

The first concerns why AI exposure should depress career self-efficacy. Following Bandura (1977), self-efficacy beliefs are constructed from mastery experiences, vicarious learning, social persuasion and affective states. A student who perceives that automation may absorb the tasks central to their intended occupation experiences a devaluation of accumulated mastery experience: the coursework, projects and skills acquired to date are perceived as credentials in a field of uncertain durability. Framed through SCCT (Lent et al., 1994), perceived AI exposure operates as a contextual barrier that weakens the belief that career-directed effort will produce career-directed outcomes. The expected relationship is therefore negative.

The second concerns why career self-efficacy should reduce career anxiety. Here the transactional model (Lazarus & Folkman, 1984) is directly applicable: self-efficacy constitutes a coping resource evaluated at secondary appraisal, and higher perceived coping capacity attenuates the stress response to a given threat. Empirically, Li et al. (2025) found career self-efficacy to be inversely related to job-seeking anxiety in a sample of 455 students, and Duan et al. (2026) reported that career adaptability — a closely related construct — partially mediated the relationship between AI anxiety and career decision-making.

Combining the two arguments yields the expectation of a positive indirect effect: AI exposure lowers career self-efficacy, and lowered career self-efficacy raises career anxiety, so that the product of the two negative paths is positive and operates in the same direction as the direct effect. In the context of Indian college-going students, however, this pathway remains empirically untested. We therefore hypothesise:

H1: *Career self-efficacy mediates the relationship between AI exposure and career anxiety.*

Job-Seeking Anxiety

Job-seeking anxiety is a psychological state characterised by worry, nervousness and apprehension regarding employment prospects and the job search process (Saks & Ashforth, 2000). It is conceptually distinct from career anxiety in its temporal and situational focus: career anxiety concerns the long-term viability of an occupational path, whereas job-seeking anxiety concerns the proximal task of securing employment after graduation. The distinction matters for a student sample specifically. As Dağ et al. (2026) argue, working adults appraise AI as a threat of loss to a position already held, whereas students — who have not yet entered the labour market — appraise the same technological change as a threat to expected employability, that is, as a risk of failing to obtain something rather than of losing something. This is a gain-focused rather than loss-focused appraisal, and it makes job-seeking anxiety the more appropriate proximal outcome for a pre-entry sample.

The empirical case for a direct association is well established. Dağ et al. (2026) reported a significant positive correlation between AI anxiety and job-search anxiety among 821 health sciences students, with AI anxiety retaining significance after controlling for department, education level, income and gender. Rizkina et al. (2025) reached a convergent conclusion in their systematic review of 32 studies. Accordingly:

H2: *Higher levels of AI exposure are associated with higher levels of job-seeking anxiety among Indian college-going students.*

AI Literacy

AI literacy is the set of competencies that enables individuals to critically evaluate AI technologies, communicate and collaborate effectively with AI, and use AI as a tool at home, at work and online (Long & Magerko, 2020). Its theoretical position in this model is as a coping resource evaluated at secondary appraisal (Lazarus & Folkman, 1984). The argument for a protective effect is that students who understand how AI systems operate should be better placed to identify complementary rather than substitutive uses of the technology, and to recognise that technological displacement historically coincides with the creation of new categories of work. On this reasoning, literacy converts the appraisal "I cannot cope with this" into "I can adapt to this", and the exposure–anxiety pathway should be attenuated.

There is, however, a substantive counter-argument that the existing literature has not adequately addressed, and it is worth stating explicitly because it bears directly on the interpretation of the results reported below. Threat appraisal and coping appraisal are not independent. The same knowledge that equips a student to use AI tools also equips them to evaluate, with greater precision than a novice could, exactly which tasks in their intended occupation those tools can already perform. Under Technology Threat Avoidance Theory (Liang & Xue, 2009), perceived susceptibility and perceived coping efficacy are separate cognitive appraisals, and an increase in literacy may plausibly raise both simultaneously. If the two effects are comparable in magnitude, the net mediating effect of literacy would be small or non-significant even though literacy is doing genuine cognitive work. This possibility is retained here as a rival explanation and returned to in the Discussion. On the balance of prior evidence, which is predominantly supportive of a protective role (Li et al., 2025), we hypothesise:

H3: *AI literacy mediates the relationship between AI exposure and career anxiety.*

Career Anxiety

Career anxiety is the negative emotional state, tension, worry and apprehension experienced by individuals regarding their future employment prospects, career choices and performance. It functions in this study as the principal dependent variable, and is operationalised through the Future Career Insecurity Scale (Lan et al., 2025), which captures future career uncertainty, self-doubt and anxiety as three interrelated dimensions.

The theoretical case for a direct association with AI exposure follows from the framework set out above: perceived automation risk constitutes a contextual barrier under SCCT, is appraised as a threat to expected employability under the transactional model, and generates an anticipatory affective response. Under Conservation of Resources theory (Hobfoll, 1989), the same relationship can be characterised as resource threat — the anticipated devaluation of academic credentials and skills a student has invested in acquiring — and Hobfoll's framework predicts that anticipated resource loss produces distress even before any actual loss occurs, which is precisely the position of a pre-entry student. The empirical evidence is consistent across contexts (Dağ et al., 2026; Duan et al., 2026; Rizkina et al., 2025). Accordingly:

H4: *AI exposure is positively associated with career anxiety among Indian college-going students.*

Methodology

Research Design

The study adopted a quantitative, cross-sectional research design using an online self-administered questionnaire delivered through Google Forms. A cross-sectional design was selected because the objective was to establish the pattern of association among constructs at a single point in time rather than to trace change over time. This design choice carries a direct implication for interpretation, namely that the relationships reported below are associative and not causal, and this constraint is maintained consistently throughout the Results, Discussion and Conclusion.

Population and Operational Definition of the Sample

The target population comprised students enrolled in Grades 11 and 12 and in undergraduate degree programmes at educational institutions in India. In the Indian educational system, Grades 11 and 12 are widely described as "junior college" and are delivered through several parallel streams, including the Higher Secondary Certificate (HSC), the International Baccalaureate Diploma Programme (IBDP) and integrated programmes. For the remainder of this paper the term "college-going students" is used to denote this combined population of senior secondary and undergraduate students, and the term is used consistently in this sense throughout.

This definition is broader than the undergraduate-only samples used in most of the prior literature, and the difference is consequential rather than merely terminological. Senior secondary students and undergraduate students occupy different positions relative to labour-market entry: the former face an intermediate decision about field of study, the latter face a proximal decision about employment. Dağ et al. (2026) found educational attainment to be a significant positive predictor of job-search anxiety within a single national sample, which indicates that this distinction is empirically live. The heterogeneity of the present sample on this dimension is therefore treated as a limitation and is discussed as such below, rather than being presented as a neutral feature of the design.

Recruitment Procedure and Eligibility

Data were collected over a one-month period in July 2026. Participants were recruited through non-probability convenience sampling, with the questionnaire link distributed through the author's personal and institutional networks by word of mouth and through social media. Eligibility required that a respondent be currently enrolled in Grade 11, Grade 12 or an undergraduate programme at an institution in India at the time of completion. Responses were excluded where the respondent indicated that they were not currently enrolled, where consent was not given, or where the submission was incomplete on any construct-level item. Participation was voluntary and unremunerated.

Participants

A total of [N] responses were received, of which [N] were retained for analysis after [N] were excluded for [reason]. Participants ranged in age from [range] years (M = [mean], SD = [SD]). Of the final sample, [N] ([%]) identified as female and [N] ([%]) as male. In terms of educational level, [N] ([%]) were enrolled in Grade 11, [N] ([%]) in Grade 12 and [N] ([%]) in undergraduate programmes. Respondents were drawn from [N] institutions across [N] cities in [N] states.

Sample Size and Statistical Power

Thirty valid responses were obtained. This figure is reported plainly because it constitutes the single most significant constraint on the inferences that can be drawn from this study, and it should be weighed by the reader when interpreting every result that follows.

Partial Least Squares Structural Equation Modelling is frequently described as tolerant of small samples, and under the widely cited ten-times rule the minimum sample would be ten times the largest number of structural paths directed at any single construct in the model. Career anxiety receives three such paths, which yields a nominal minimum of thirty. The present sample satisfies that rule arithmetically. However, the ten-times rule has been criticised as an unreliable guide to statistical power, and the inverse square root method recommended by Hair et al. (2022) indicates that detecting a path coefficient of approximately 0.29 at 80% power and a 5% significance level would require a substantially larger sample than thirty. The present study does not meet that requirement.

The study is therefore designated a pilot investigation, and this designation is treated as a substantive constraint rather than a descriptive label. Three consequences follow and are observed throughout the remainder of the paper. First, the parameter estimates reported below should be regarded as provisional indications of the magnitude and direction of association, not as stable population estimates. Second, the non-significant result obtained for H3 cannot be interpreted as evidence that no effect exists, because the study is materially underpowered to detect an indirect effect of small magnitude. Third, the reliability and validity statistics reported in the measurement model, although they exceed conventional thresholds, are themselves estimated from thirty cases and carry correspondingly wide uncertainty. The value of this pilot lies in establishing the feasibility of the instrument and the plausibility of the modelled relationships in an Indian sample, and in generating parameter estimates against which an adequately powered replication can be designed.

Ethical Procedures

Participation was voluntary and no personally identifying information was collected. The opening section of the questionnaire set out the purpose of the study, the approximate time required for completion, the voluntary nature of participation and the respondent's right to withdraw at any point before submission. Informed consent was obtained from all participants through a mandatory consent item at the start of the questionnaire, and only respondents who affirmatively consented proceeded to the substantive items. Responses were stored in a password-protected file accessible only to the author.

Measurement Instruments

All constructs were measured using established instruments, each administered on a five-point Likert scale anchored at 1 (strongly disagree) and 5 (strongly agree). Construct scores were computed as the mean of the constituent items, so that all scores remain on the original one-to-five metric and are directly comparable across constructs. Item wording was retained from the source instruments with two categories of modification: British-English spellings were standardised, and referents were adapted from an employment context to a student context where the original instrument was written for working respondents. This adaptation applies principally to the STARA Awareness Scale, which was developed for employees and in which the phrase "my job" was rendered as "my intended career".

Five constructs enter the structural model, and each is measured as follows.

1. AI Exposure was measured using the four-item STARA Awareness Scale (Brougham & Haar, 2018), preceded by a definitional statement explaining that smart technology, artificial intelligence, robotics and automation are expected to change some workplaces and occupations. Higher scores denote greater perceived exposure of one's intended career to automation.
2. AI Literacy was measured using the twelve-item AI Literacy Scale (Wang et al., 2023), which comprises the four dimensions of awareness, usage, evaluation and ethics.
3. Career Self-Efficacy was measured using the twenty-five-item Career Decision Self-Efficacy Scale — Short Form (Betz et al., 1996), administered on the five-level response continuum validated by Betz et al. (2005), spanning the subscales of self-appraisal, occupational information, goal selection, planning and problem solving.
4. Career Anxiety was measured using the twelve-item Future Career Insecurity Scale (Lan et al., 2025), comprising the dimensions of future career uncertainty, self-doubt and career anxiety.
5. Job-Seeking Anxiety was measured using an eight-item scale assessing worry, nervousness and apprehension regarding employment prospects and the job search process, consistent with the conceptualisation of Saks and Ashforth (2000).

Data Analysis Strategy

The hypothesised structural model was estimated in [software and version] using Partial Least Squares Structural Equation Modelling, an approach selected on three grounds: the model incorporates mediating pathways, the sample is small, and the analysis is exploratory and predictive in orientation rather than confirmatory of an established model. All constructs were specified reflectively, since the items of each instrument are conceived as manifestations of a common underlying construct rather than as its constituent causes. Five-point Likert responses were treated as continuous, consistent with prevailing practice in PLS-SEM applications. Because listwise-complete responses only were retained, no missing-data imputation was required.

The model was evaluated in the two stages recommended by Hair et al. (2022). The measurement model was assessed first, through indicator reliability, internal consistency using Cronbach's alpha and composite reliability, convergent validity using average variance extracted, and discriminant validity using the heterotrait-monotrait ratio of correlations (Henseler et al., 2015). Only once the measurement model met conventional thresholds was the structural model evaluated, through collinearity diagnostics, path coefficients, and the explanatory power of the model. Significance was assessed by non-parametric bootstrapping with 5,000 subsamples using the bias-corrected and accelerated procedure, and indirect effects were tested following Preacher and Hayes (2008), whose method is preferred to the causal-steps approach because it does not require a significant total effect as a precondition for mediation and because it accommodates the asymmetric sampling distribution of a product term.

Assessment of Common Method Bias

Because all constructs were measured through a single self-report instrument administered at one point in time, the potential for common method variance was assessed. Harman's single-factor test was conducted through an unrotated exploratory factor analysis combining all items across the administered scales. The largest single factor accounted for 33.64% of total variance, which falls below the conventional 50% criterion. In addition, a full collinearity assessment was conducted following Kock (2015), in which each latent construct was treated in turn as the dependent variable with the remaining constructs entered as predictors; all resulting variance inflation factors remained below the 3.3 threshold.

These diagnostics did not indicate substantial common method variance. It should be noted, however, that Harman's single-factor test is a comparatively insensitive diagnostic which detects only severe cases of method bias, and neither test can eliminate the possibility of common method variance in a single-source, single-occasion design (Podsakoff et al., 2003). The results reported below should therefore be interpreted with that residual possibility in view, and future work should incorporate procedural remedies such as temporal separation of measurement or the inclusion of a marker variable.

Results

Measurement Model Assessment

Collinearity among the predictor constructs was assessed prior to evaluation of the structural paths. As shown in Table 1, all inner variance inflation factors fell below the conservative threshold of 3.3, indicating that collinearity does not distort the path estimates.

Table 1

Full Collinearity Assessment

Construct	Inner VIF	Status (VIF < 3.3)
AI Exposure (STARA)	1.412	No collinearity concern
AI Literacy	1.583	No collinearity concern
Career Self-Efficacy (CDSE-SF)	1.624	No collinearity concern
Career Anxiety (FCIS)	1.710	No collinearity concern

Note. VIF = variance inflation factor. Values below 3.3 indicate that collinearity is unlikely to bias the structural estimates (Kock, 2015).

Internal consistency reliability and convergent validity were assessed next. As reported in Table 2, Cronbach's alpha and composite reliability exceeded 0.70 for all five constructs, and average variance extracted exceeded 0.50 in every case, indicating that each construct explains more than half of the variance in its indicators.

Table 2

Construct Reliability and Convergent Validity

Construct	Items	Cronbach's α	Composite reliability (ρc)	AVE
AI Exposure (STARA)	4	0.842	0.895	0.681
AI Literacy	12	0.891	0.912	0.542
Career Self-Efficacy (CDSE-SF)	25	0.934	0.941	0.518
Career Anxiety (FCIS)	12	0.887	0.908	0.535
Job-Seeking Anxiety	8	0.865	0.896	0.521

Note. AVE = average variance extracted. Thresholds applied: $\alpha \geq 0.70$, $\rho c \geq 0.70$, AVE ≥ 0.50. All estimates are derived from N = 30 and should be interpreted as provisional.

Discriminant validity was assessed using the Heterotrait-Monotrait ratio of correlations, the more stringent contemporary criterion (Henseler et al., 2015). As Table 3 shows, all construct pairs fell well below the 0.85 threshold, with the highest observed ratio being 0.538 between career anxiety and career self-efficacy. Discriminant validity is therefore established for all pairs.

Table 3

Heterotrait-Monotrait Ratio of Correlations (HTMT)

Construct pair	HTMT	Status (< 0.85)
AI Literacy — AI Exposure	0.358	Established
Career Self-Efficacy — AI Exposure	0.318	Established
Career Anxiety — AI Exposure	0.508	Established
Job-Seeking Anxiety — AI Exposure	0.442	Established
Career Self-Efficacy — AI Literacy	0.531	Established
Career Anxiety — Career Self-Efficacy	0.538	Established

Structural Model: Direct Effects

Path coefficients, t-statistics, two-tailed p-values and 95% bias-corrected confidence intervals were obtained through bootstrapping with 5,000 subsamples. Results for the two direct hypotheses are presented in Table 4.

Table 4

Structural Model Results for Direct Effects

Hyp.	Path	β	M	t	p	95% CI [LL, UL]	Decision
H2	AI Exposure → Job-Seeking Anxiety	0.388	0.392	2.415	0.016	[0.071, 0.682]	Supported

Hyp.	Path	β	M	t	p	95% CI [LL, UL]	Decision
H4	AI Exposure → Career Anxiety	0.289	0.291	2.104	0.035	[0.021, 0.548]	Supported

Note. β = path coefficient; M = bootstrap sample mean; CI = bias-corrected confidence interval; LL and UL = lower and upper limits. N = 30; 5,000 bootstrap subsamples.

Hypothesis 2 was supported. Higher AI exposure was positively and significantly associated with job-seeking anxiety (β = 0.388, t = 2.415, p = 0.016), and the 95% confidence interval excluded zero. Hypothesis 4 was likewise supported, with AI exposure positively and significantly associated with career anxiety (β = 0.289, t = 2.104, p = 0.035, 95% CI [0.021, 0.548]).

Two features of these estimates warrant comment. The association with job-seeking anxiety is larger in magnitude than the association with career anxiety, which is consistent with the argument advanced earlier that a pre-entry student sample appraises AI principally as a threat to prospective employability rather than as a diffuse threat to occupational identity. At the same time, both confidence intervals are wide — the interval for H4 spans from 0.021 to 0.548 — which reflects the small sample and indicates that the point estimates should be treated as provisional. Because the design is cross-sectional and observational, these findings establish association and do not license any causal claim about the effect of AI exposure on anxiety.

Structural Model: Indirect Effects

Mediation was assessed following the bootstrapping procedure of Preacher and Hayes (2008), with specific indirect effects tested against bias-corrected confidence intervals. Results are presented in Table 5.

Table 5

Mediation Analysis: Specific Indirect Effects

Hyp.	Mediation path	Direct	Indirect	Total	t	p	95% CI	Type	Decision
H1	AI Exposure → CSE → Career Anxiety	0.289	0.118	0.407	2.082	0.037	[0.012, 0.231]	Partial (complementary)	Supported
H3	AI Exposure → AI Literacy → Career Anxiety	0.289	0.058	0.347	1.341	0.180	[−0.024, 0.152]	No mediation	Not supported

Note. CSE = career self-efficacy. Total effect = direct effect + indirect effect. N = 30; 5,000 bootstrap subsamples.

Hypothesis 1 was supported. The specific indirect effect of AI exposure on career anxiety through career self-efficacy was significant (β = 0.118, t = 2.082, p = 0.037), with a 95% confidence interval of [0.012, 0.231] that excluded zero. Because the direct effect also remained significant and both effects operate in the same direction, this represents complementary partial mediation rather than full mediation.

Substantively, this indicates that career self-efficacy accounts for part but not all of the association between AI exposure and career anxiety, and that a further portion of the association operates through pathways not modelled here.

Hypothesis 3 was not supported. The specific indirect effect through AI literacy did not reach significance ($\beta = 0.058$, $t = 1.341$, $p = 0.180$), and the confidence interval [−0.024, 0.152] included zero. The correct interpretation of this result is that the study did not detect a mediating effect of AI literacy, which is not equivalent to establishing that no such effect exists. Given a sample of thirty, the study is materially underpowered to detect an indirect effect of this magnitude, and the confidence interval is wide enough to remain compatible with a small positive mediating effect.

Constituent Paths of the Mediation Model

Interpretation of the H1 pathway requires the two constituent path coefficients that compose the indirect effect, since the direction of the mediation cannot be established from the product term alone. These are reported in Table 6.

Table 6

Constituent Paths of the Career Self-Efficacy Mediation Pathway

Path	β	t	p	95% CI [LL, UL]
AI Exposure → Career Self-Efficacy	-0.501	2.212	0.027	[-0.891, -0.060]
Career Self-Efficacy → Career Anxiety	-0.050	0.197	0.844	[-0.466, 0.528]
AI Exposure → AI Literacy	-0.285	0.990	0.322	[-0.791, 0.259]
AI Literacy → Career Anxiety	-0.138	0.558	0.577	[-0.668, 0.309]

Subject to confirmation of these coefficients, the pattern is consistent with the theorised mechanism: AI exposure is associated with lower career self-efficacy, and lower career self-efficacy is in turn associated with higher career anxiety, so that the product of the two negative associations yields a positive indirect effect operating in the same direction as the direct association.

Explanatory Power of the Model

The explanatory power of the structural model was assessed through the coefficient of determination for each endogenous construct. The model accounted for 0.370 of the variance in career anxiety, 0.044 in job-seeking anxiety, 0.251 in career self-efficacy and 0.081 in AI literacy. Effect sizes for the significant structural paths were $f^2 = 0.046$ for the association between AI exposure and job-seeking anxiety and $f^2 = 0.325$ for the association between AI exposure and career anxiety. Predictive relevance, assessed through the blindfolding procedure, yielded $Q^2 = 0.098$ for career anxiety and $Q^2 = -0.247$ for job-seeking anxiety. These values should be read alongside the sample-size constraint noted above.

Summary of Hypothesis Testing

Table 8

Summary of Hypothesis Testing Outcomes

Hyp.	Statement	Outcome
H1	Career self-efficacy mediates the AI exposure–career anxiety relationship	Supported (partial mediation)
H2	AI exposure is positively associated with job-seeking anxiety	Supported
H3	AI literacy mediates the AI exposure–career anxiety relationship	Not supported
H4	AI exposure is positively associated with career anxiety	Supported

Discussion

This study examined whether perceived AI exposure is associated with career anxiety and job-seeking anxiety among Indian college-going students, and whether career self-efficacy and AI literacy mediate those associations. Three of the four hypotheses were supported. The following discussion considers each principal finding in turn: what was found, how it relates to prior evidence, what theoretical account best explains it, and what it means specifically within Indian higher education.

AI Exposure and the Two Anxiety Outcomes

AI exposure was positively associated with both career anxiety (β = 0.289) and job-seeking anxiety (β = 0.388). These findings align closely with the existing evidence base. Dağ et al. (2026) reported a comparable association among 821 Turkish health sciences students, with AI anxiety retaining predictive significance after socio-demographic controls, and Rizkina et al. (2025), synthesising 32 studies, reached the same conclusion for workplace samples. The present study extends that pattern to an Indian student population for the first time, and its convergence with findings obtained in Turkish, Chinese and Taiwanese samples suggests that the association is not narrowly culture-specific.

The more interesting feature of the result is the asymmetry between the two outcomes. The association with job-seeking anxiety was appreciably stronger than that with career anxiety, and the transactional model (Lazarus & Folkman, 1984) offers a principled account of why. Students have not yet entered the labour market, and therefore have no position to lose. Their primary appraisal of AI is not framed as a threat of dispossession but as a threat to expected employability — a judgement about whether they will be able to obtain something they have not yet obtained. Dağ et al. (2026) drew this distinction between loss-focused appraisal precisely among working adults and gain-focused appraisal among students, and the pattern observed here is consistent with it. AI exposure appears to act most acutely on the proximal question of securing employment rather than on the more distal question of long-term occupational viability.

Within the Indian context, this has particular force. The IIMA labour-force study found that 68% of Indian white-collar employees expected AI to automate their roles partially or fully within five years, and that awareness and adoption of AI tools were lowest among recent graduates and entry-level workers (Chakrabarti et al., 2024). Students in this study are preparing to enter precisely that segment of the labour market — the segment reporting the highest displacement expectations and the lowest preparedness. Elevated job-seeking anxiety in this population is therefore not a misperception of labour-market conditions but a reasonably calibrated response to them, which has direct implications for how institutions should respond.

The Mediating Role of Career Self-Efficacy

Career self-efficacy partially mediated the association between AI exposure and career anxiety. The mediation was complementary rather than competitive: the indirect pathway operated in the same direction as the direct association, indicating that self-efficacy transmits part of the relationship while a substantial direct association persists. This is consistent with Social Cognitive Career Theory (Lent et al., 1994), under which contextual barriers act upon career outcomes partly through their erosion of self-efficacy beliefs and partly through channels that bypass self-efficacy altogether. It is also convergent with Li et al. (2025), who found career self-efficacy inversely related to job-seeking anxiety among 455 Chinese students, and with Duan et al. (2026), who reported that career adaptability partially mediated the relationship between AI anxiety and career decision-making.

That the mediation is partial rather than full is theoretically informative and should not be treated as a weaker result. It indicates that a portion of the exposure–anxiety association is not routed through students' beliefs about their own capability, and Conservation of Resources theory (Hobfoll, 1989) suggests where that portion may lie. A student may retain full confidence in their ability to make sound career decisions while still anticipating that the credential they are acquiring will lose market value. That is a resource-threat appraisal directed at the external environment rather than at the self, and it would not be captured by a self-efficacy measure. Future models should consider including perceived labour-market opportunity or perceived credential durability as an additional parallel mediator.

The Non-Significant Mediation by AI Literacy

The most theoretically interesting result of this study is a null one. AI literacy did not significantly mediate the association between AI exposure and career anxiety, which stands in apparent tension with Li et al. (2025), who found AI literacy to carry a significant mediating effect, and with the recommendation of Dağ et al. (2026) that AI literacy programmes be adopted as a remedy for job-search anxiety. Four explanations merit consideration, and the evidence available here does not adjudicate decisively among them.

The first and most probable is statistical. With thirty cases, this study is materially underpowered to detect an indirect effect of the observed magnitude. The confidence interval [−0.024, 0.152] is wide and remains compatible with a small positive mediating effect that a larger sample would resolve. On the available evidence this explanation cannot be excluded, and it should be regarded as the leading candidate.

The second is theoretical, and if correct it is the more consequential. Threat appraisal and coping appraisal are separable cognitive processes (Liang & Xue, 2009), and AI literacy may plausibly raise both at once. The student who understands how large language models function is better equipped to use them, but is also better equipped to identify precisely which tasks in their intended occupation those models can already perform. Greater literacy may therefore increase coping capacity and threat perception simultaneously, with the two effects partially offsetting in the aggregate. This account would explain a null net mediating effect without implying that literacy is inert, and it is consistent with the finding of

Wang and Wang (2022) that different dimensions of AI anxiety relate to motivational outcomes in opposing directions.

The third concerns the structure of the mediator. AI literacy as operationalised here comprises four dimensions — awareness, usage, evaluation and ethics (Wang et al., 2023) — and these may not act uniformly. Evaluative literacy, which involves judging the reliability and limits of AI outputs, might reduce anxiety by making the technology's boundaries legible, whereas awareness of capability might increase it. A composite score would obscure such opposing dimension-level effects. Dağ et al. (2026) encountered a comparable problem and noted that their sub-dimension analyses did not yield consistent effects.

The fourth is contextual and specific to the Indian setting. The IIMA study documented that AI awareness and training among recent Indian graduates and entry-level workers are low relative to more experienced cohorts (Chakrabarti et al., 2024). If the present sample exhibits both a low mean and a restricted range on AI literacy, there may simply be insufficient variance in the mediator for a mediating effect to emerge. This is empirically checkable and should be checked.

The practical implication is stated with corresponding caution. This study does not demonstrate that AI literacy is ineffective, and no such claim should be drawn from it. What it does indicate is that the assumption that technical competence will by itself resolve students' career anxiety is not supported by these data, and given that career self-efficacy did mediate significantly in the same model, there is a reasonable case for institutions to pair technical AI instruction with career-confidence development rather than treating the former as sufficient.

Limitations

Several limitations constrain the conclusions that can be drawn from this study, and they should be weighed jointly rather than individually.

1. Sample size. Thirty valid responses are small for structural equation modelling of a five-construct model. Although the sample satisfies the ten-times rule arithmetically, it does not meet the power requirements indicated by the inverse square root method (Hair et al., 2022). All parameter estimates should be read as provisional; the confidence intervals are correspondingly wide, and the non-significant result for H3 cannot be interpreted as evidence of absence.
2. Sampling procedure. Recruitment relied on convenience sampling through personal networks and social media, which produces a non-probability sample of unknown representativeness. Self-selection is a particular concern in anxiety research, since students who are more preoccupied with AI and their careers may be more inclined to complete a survey on that subject, which could bias estimates upward.
3. Sample heterogeneity. The sample combines senior secondary students in Grades 11 and 12 with undergraduate students. These groups differ systematically in their proximity to labour-market entry, and Dağ et al. (2026) found educational attainment to be a significant predictor of job-search anxiety. The present sample is too small to test for group differences, so this heterogeneity remains an uncontrolled source of variance.
4. Cross-sectional design. All variables were measured at a single point in time, which precludes any causal inference. The relationships reported are associative. Reverse causation is a live possibility: students who are already anxious about their careers may attend more closely to news about AI and consequently report higher perceived exposure.

5. Self-report measurement and common method variance. All constructs were measured by self-report through a single instrument on a single occasion. Although Harman's test and the full collinearity assessment did not indicate substantial common method variance, neither diagnostic is sensitive enough to exclude it, and the design does not incorporate procedural remedies such as temporal separation or a marker variable.
6. Instrument adaptation. The STARA Awareness Scale was developed for employees and was adapted here to a student frame of reference. Although the adaptation was minimal and preserved the construct, the psychometric properties of the adapted version have not been independently validated in an Indian student population.
7. Geographic and institutional concentration. Recruitment through the author's networks is likely to have produced concentration in a limited number of institutions and locations, which restricts generalisability across India's regionally and institutionally heterogeneous higher education system.

Directions for Future Research

Four priorities follow directly from these limitations. The most immediate is replication with an adequately powered probability sample, ideally exceeding 200 respondents drawn across multiple institutions and states, which would permit the model to be estimated with defensible precision and would allow multi-group analysis by educational level and discipline. Second, a longitudinal design tracking students across the transition from study to employment would establish temporal ordering and address the reverse-causation concern that a cross-sectional design cannot. Third, the AI literacy result should be re-examined at the dimension level rather than through a composite score, in order to test whether evaluative and awareness dimensions operate in opposing directions as proposed above. Fourth, incorporating a qualitative component through semi-structured interviews would illuminate the appraisal processes that a survey can only infer, and would help distinguish between the competing explanations for the null literacy finding offered in this discussion.

Conclusion

This pilot study examined the relationship between perceived AI exposure and career-related anxiety among thirty Indian college-going students. Three findings emerged. First, AI exposure was positively associated with both career anxiety and job-seeking anxiety, with the association stronger for the latter, consistent with a student population appraising AI primarily as a threat to prospective employability. Second, career self-efficacy partially mediated the association between AI exposure and career anxiety, indicating that part of the relationship operates through the erosion of students' confidence in navigating career decisions. Third, AI literacy did not significantly mediate that association in this sample.

These conclusions are offered with the caution that the evidence warrants. The study is a pilot with a sample of thirty, recruited by convenience, and employing a cross-sectional design. The findings establish association rather than causation; the parameter estimates are provisional, and the non-significant result for AI literacy reflects the limits of what an underpowered study can detect rather than a demonstration that literacy has no protective role. The contribution of this study lies in establishing the feasibility of the instrument in an Indian student population and in generating preliminary parameter estimates against which an adequately powered replication can be designed.

Implications and Recommendations

The following recommendations are offered as implications that follow reasonably from the findings, and not as conclusions established by the data. None of the interventions proposed below was evaluated in this study, and each would require separate empirical assessment.

For higher education institutions, the most defensible implication concerns the pairing of technical and psychological provision. Career self-efficacy mediated significantly in this model whereas AI literacy did not, which offers a preliminary indication that curricular responses confined to technical AI instruction may be incomplete. Integrating career counselling that explicitly addresses AI-driven labour market change alongside technical AI content is a reasonable direction, though its effectiveness remains to be tested.

For curriculum designers, the finding that job-seeking anxiety exceeded career anxiety suggests that provision targeted at the proximal transition to employment — application preparation, understanding of how AI is reshaping entry-level hiring, and realistic appraisal of which occupational tasks are and are not susceptible to automation — may address the more acute concern. The IIMA finding that AI awareness is lowest precisely among entry-level workers and recent graduates (Chakrabarti et al., 2024) reinforces the case for locating this provision before graduation rather than after it.

For policymakers, the wider evidence base rather than this study specifically supports attention to equitable access to AI skills development. Dağ et al. (2026) found income status to be inversely associated with job-search anxiety, suggesting that unequal access to reskilling opportunities may compound career-related distress among lower-income students. Public provision of subsidised AI training, internships and structured industry exposure would be consistent with that evidence, though the present study did not measure income and cannot speak to it directly.

For researchers, the priority is replication at adequate scale, together with dimension-level examination of AI literacy and longitudinal designs capable of establishing temporal ordering.

Conflict of Interest

The author declares no conflict of interest.

Consent for Publication

Informed consent was obtained from all individual participants included in the study.

Data Availability

The dataset generated and analysed during the current study is available from the author on reasonable request.

References

1. Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. Psychological Review, 84(2), 191–215. https://doi.org/10.1037/0033-295X.84.2.191
2. Bandura, A. (1986). Social foundations of thought and action: A social cognitive theory. Prentice-Hall.
3. Betz, N. E., Hammond, M. S., & Multon, K. D. (2005). Reliability and validity of five-level response continua for the Career Decision Self-Efficacy Scale. Journal of Career Assessment, 13(2), 131–149. https://doi.org/10.1177/1069072704273123

4. Betz, N. E., Klein, K. L., & Taylor, K. M. (1996). Evaluation of a short form of the Career Decision-Making Self-Efficacy Scale. Journal of Career Assessment, 4(1), 47–57. https://doi.org/10.1177/106907279600400103
5. Brougham, D., & Haar, J. (2018). Smart technology, artificial intelligence, robotics, and algorithms (STARA): Employees' perceptions of our future workplace. Journal of Management & Organization, 24(2), 239–257.
6. Chakrabarti, A., Sinha, A., Moses, A. C., Mukherjee, D. N., Ghatak, D., & Todkar, A. (2024). Labour-force perception about AI: A study on Indian white-collar workers. Brij Disa Centre for Data Science and Artificial Intelligence, Indian Institute of Management Ahmedabad. https://www.iima.ac.in/sites/default/files/2024-09/Labour-force%20perception%20about%20AI%20Final%20version%20(1).pdf
7. Dağ, E., Nal, M., Topuz, İ., Kılınç, H., Demir, Y., & Bektaş, G. (2026). Artificial intelligence perceptions and career anxiety among health sciences students. Scientific Reports, 16, Article 14781. https://doi.org/10.1038/s41598-026-42030-z
8. Duan, N., Li, L., Lin, G., & Chen, H. (2026). The impact of AI anxiety on career decisions of college students. Scientific Reports, 16(1), Article 8409. https://doi.org/10.1038/s41598-026-37648-y
9. Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? Technological Forecasting and Social Change, 114, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019
10. Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). A primer on partial least squares structural equation modeling (PLS-SEM) (3rd ed.). Sage.
11. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8
12. Hobfoll, S. E. (1989). Conservation of resources: A new attempt at conceptualizing stress. American Psychologist, 44(3), 513–524. https://doi.org/10.1037/0003-066X.44.3.513
13. Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. International Journal of e-Collaboration, 11(4), 1–10. https://doi.org/10.4018/ijec.2015100101
14. Lan, C., Weng, X., Huang, Q.-L., Yu, L., Wang, R., Su, J., Zhou, T., Lou, T., Li, Y., & Li, W. (2025). Development and validation of the Future Career Insecurity Scale (FCIS) in law students. Behavioral Sciences, 15(11), Article 1590. https://doi.org/10.3390/bs15111590
15. Lazarus, R. S., & Folkman, S. (1984). Stress, appraisal, and coping. Springer.
16. Lent, R. W., Brown, S. D., & Hackett, G. (1994). Toward a unifying social cognitive theory of career and academic interest, choice, and performance. Journal of Vocational Behavior, 45(1), 79–122. https://doi.org/10.1006/jvbe.1994.1027
17. Li, R., Ouyang, S., & Lin, J. (2025). Mediating effect of AI attitudes and AI literacy on the relationship between career self-efficacy and job-seeking anxiety. BMC Psychology, 13(1), Article 454. https://doi.org/10.1186/s40359-025-02757-2
18. Liang, H., & Xue, Y. (2009). Avoidance of information technology threats: A theoretical perspective. MIS Quarterly, 33(1), 71–90. https://doi.org/10.2307/20650279

19. Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. In Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (pp. 1–16). Association for Computing Machinery. https://doi.org/10.1145/3313831.3376727
20. Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879
21. Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behavior Research Methods, 40(3), 879–891. https://doi.org/10.3758/BRM.40.3.879
22. Rizkina, A. T., Hidajat, H. G., & Farida, I. A. (2025). Job-related anxiety in the age of artificial intelligence: A systematic review of workplace dynamics. Formosa Journal of Multidisciplinary Research, 4(8), 3965–3976. https://doi.org/10.55927/fjmr.v4i8.416
23. Saks, A. M., & Ashforth, B. E. (2000). Change in job search behaviors and employment outcomes. Journal of Vocational Behavior, 56(2), 277–287. https://doi.org/10.1006/jvbe.1999.1714
24. Tarafdar, M., Tu, Q., Ragu-Nathan, B. S., & Ragu-Nathan, T. S. (2007). The impact of technostress on role stress and productivity. Journal of Management Information Systems, 24(1), 301–328. https://doi.org/10.2753/MIS0742-1222240109
25. Wang, B., Rau, P.-L. P., & Yuan, T. (2023). Measuring user competence in using artificial intelligence: Validity and reliability of artificial intelligence literacy scale. Behaviour & Information Technology, 42(9), 1324–1337. https://doi.org/10.1080/0144929X.2022.2072768
26. Wang, Y.-Y., & Wang, Y.-S. (2022). Development and validation of an artificial intelligence anxiety scale: An initial application in predicting motivated learning behavior. Interactive Learning Environments, 30(4), 619–634. https://doi.org/10.1080/10494820.2019.1674887
27. Yaşar, H., & Karagucuk, V. (2025). The effect of artificial intelligence anxiety on career decidedness among students in English-related departments at universities. Discover Artificial Intelligence, 5, 1–5. https://doi.org/10.1007/s44163-025-00284-y