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The Influence of AI Literacy, AI Attitude, and Career Self-Efficacy on Job-Seeking Anxiety among Final-Year University Students

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Abstract: The study entitled "The Influence of Career Self-Efficacy on Job Seeking Anxiety: The Mediating Role of AI Attitude and AI Literacy among Final-Year University Students" examines final-year students as the research object to understand psychological and technological factors influencing anxiety during the job search process. This study aims to analyze the impact of Career Self-Efficacy on Job Seeking Anxiety and to evaluate the mediating roles of AI Literacy and AI Attitude. A quantitative approach with a causal associative design was employed, involving 120 respondents who completed a structured questionnaire, and the data were analyzed using SEM-PLS. The results show that Career Self-Efficacy has a significant negative effect on Job Seeking Anxiety, while AI Literacy and AI Attitude also directly reduce anxiety related to job searching. However, neither AI Literacy nor AI Attitude mediates the relationship between Career Self-Efficacy and Job Seeking Anxiety, and no chain mediation effect was found. The study concludes that confidence in career-related abilities is the primary factor that decreases job-seeking anxiety, whereas AI Literacy and AI Attitude serve as supportive factors that contribute directly without acting as mediators.

Keyword: Career Self-Efficacy, Job Seeking Anxiety, AI Literacy, AI Attitude, Final-Year Students.

INTRODUCTION

The rapid development of *Artificial Intelligence* over the past decade has reshaped how people learn, work, and make decisions across education, creative industries, public services, and labor markets. For final-year university students who stand at the threshold of employment, this transformation presents both opportunity and uncertainty. On one hand, advanced systems that generate text, analyze data, and support decision-making promise new efficiencies and novel career pathways; on the other, the accelerating diffusion of automation raises concerns about employability, competitiveness, and preparedness for technology-intensive roles (Russell et al., 2021; OECD, 2023). Within this context, anxiety linked to the job search process can intensify, particularly when students must navigate selection procedures while simultaneously adapting to tools and practices enabled by *Artificial Intelligence*. Such anxiety is not merely a transient emotional state but can impede preparation behaviors, reduce the quality of applications, and undermine performance in interviews and related assessments (Tri et al., 2021).

A growing stream of scholarship suggests that psychological resources and technology-related competencies play decisive roles in shaping how students experience this transition. A central construct in vocational psychology is *Career Self-Efficacy*, defined as the individual's belief in their capability to perform tasks required for career exploration, planning, decision-making, and barrier management. Higher levels of *Career Self-Efficacy* are generally associated with lower anxiety during career transitions because confident individuals are more likely to appraise challenges as manageable and to deploy effective coping and preparatory strategies (Juniarti & Adrian, 2022; Lasmini et al., 2024). In parallel, as digitalization deepens, two technology-focused constructs have become increasingly salient: *AI Literacy* and *AI Attitude*. *AI Literacy* refers to the knowledge, critical understanding, and practical skills needed to interpret, evaluate, and ethically use *Artificial Intelligence*—from conceptual comprehension to applied tool use and recognition of limitations. *AI Attitude* captures cognitive, affective, and conative evaluations of *Artificial Intelligence*, including perceived benefits, perceived risks, acceptance, and trust (Long & Magerko, 2020; Schepman & Rodway, 2020). Together, these technology-related factors may influence how students harness *Artificial Intelligence* in career activities such as optimizing résumés, preparing for interviews, and mapping job opportunities, potentially mitigating anxiety by increasing perceived control and efficacy in the job search.

Theoretically, the relationships among these variables can be grounded in established models. The *Theory of Planned Behavior* posits that beliefs shape attitudes, which then inform intentions and behavior; in technology contexts, the *Technology Acceptance Model* emphasizes perceived usefulness and ease of use as antecedents of acceptance (Ajzen, 1991; Davis, 1989). From a social-cognitive perspective, efficacy beliefs influence emotional regulation and effort expenditure, thereby affecting outcomes under stress. Extending these logics to the present phenomenon, one may expect students with strong *Career Self-Efficacy* to experience less *Job Seeking Anxiety*, and for *AI Literacy* and *AI Attitude* to either directly reduce anxiety or mediate the pathway from efficacy to anxiety by reframing *Artificial Intelligence* as an empowering ally rather than a threat (Kang et al., 2024; Hair et al., 2019). Nevertheless, empirical findings in different settings remain mixed, and much of the prior work has been conducted outside the Indonesian context, calling for evidence that reflects local educational, cultural, and market conditions.

Addressing this gap, the present study focuses on final-year students as the research object and examines four core constructs in a single explanatory model: *Career Self-Efficacy* (independent variable), *Job Seeking Anxiety* (dependent variable), *AI Attitude* (mediator), and *AI Literacy* (mediator). Operationally, *Career Self-Efficacy* is captured through indicators such as self-assessment, information seeking, goal setting, planning, and barrier coping; *Job Seeking Anxiety* encompasses concerns about application outcomes, interview apprehension, uncertainty about employment prospects, and social-economic pressures during the search; *AI Attitude* includes beliefs about benefits and risks, willingness to adopt, and trust; *AI Literacy* covers conceptual understanding, awareness of social impact, practical capability, and ethical conduct. By articulating these operational definitions within a coherent framework, the study enables rigorous measurement and clear interpretation of pathways among psychological and technological factors in the job search experience.

Empirically, the study employs a quantitative, causal-associative design using a structured Likert-type questionnaire administered to 120 respondents and analyzed with

Structural Equation Modeling using the *Partial Least Squares* approach. This strategy is appropriate for testing complex models with multiple mediators and for samples of modest size, while relaxing strict normality assumptions and providing robust estimates of direct and indirect effects. Within this design, model assessment proceeds through outer-model evaluation for reliability and validity, followed by inner-model evaluation for explanatory power and path significance, thereby enabling comprehensive tests of the hypothesized relationships among *Career Self-Efficacy*, *AI Literacy*, *AI Attitude*, and *Job Seeking Anxiety* (Hair et al., 2019).

In light of the foregoing, the objective contains the guiding questions that the discussion must explain and the conclusion must answer: (1) Does *Career Self-Efficacy* exert a negative effect on *Job Seeking Anxiety* among final-year students? (2) Do *AI Literacy* and *AI Attitude* mediate—or otherwise shape—the relationship between *Career Self-Efficacy* and *Job Seeking Anxiety*? (3) To what extent do *AI Literacy* and *AI Attitude* independently reduce *Job Seeking Anxiety* by fostering constructive engagement with *Artificial Intelligence* during job search activities? By addressing these questions in a single integrated model, the study seeks to clarify whether internal psychological resources or technology-related competencies are the primary levers for reducing anxiety, and whether their influences are additive, mediational, or both.

This contribution is both practical and theoretical. Practically, identifying the relative weight of *Career Self-Efficacy*, *AI Literacy*, and *AI Attitude* can guide universities in designing interventions that blend career readiness coaching with targeted *Artificial Intelligence* training, thereby equipping students to navigate recruitment processes with confidence and skill. Theoretically, testing mediation and direct paths in an Indonesian student population enriches the literature by situating established constructs within a local context that features distinct cultural norms, educational structures, and technology adoption patterns. In sum, by integrating psychological and technological perspectives, the study endeavors to illuminate the mechanisms that heighten or alleviate *Job Seeking Anxiety* in the era of *Artificial Intelligence*, and to furnish evidence-based recommendations for enhancing student readiness for a rapidly evolving labor market (Schepman & Rodway, 2020; Wu et al., 2024).

METHOD

This study employed a quantitative research approach with a causal–associative design to analyze the direct and indirect relationships among *Career Self-Efficacy*, *AI Literacy*, *AI Attitude*, and *Job Seeking Anxiety*. The causal–associative method was selected because the study aimed not only to describe the existing conditions of the variables but also to explain the patterns of influence and causal pathways among them, particularly the mediating mechanisms that might connect psychological and technological factors within the job-seeking process (Sugiyono, 2013). This design is well aligned with research objectives that examine complex behavioral constructs and their interconnectedness, especially in the contemporary context of rapid technological advancement.

The research was carried out online and targeted final year active undergraduate students in Cirebon who had prior experience using *Artificial Intelligence* tools. Conducting the study online ensured wide geographic reach, efficiency, and accessibility, enabling participation from students across several universities while reducing logistical constraints. Data collection was conducted from November to December 2025, allowing respondents adequate time to complete the instrument and ensuring the data captured reflected students' current engagement with emerging forms of AI integration in academic and career-related tasks.

The population in this study encompassed all final year active undergraduate students in Indonesia who have interacted with or utilized AI technology for learning or career preparation. However, due to the vast and dispersed nature of this population, the sampling strategy employed was probability-based *cluster sampling*. This method divides the population into smaller, naturally occurring groups or clusters, such as university faculties or study programs, from which the sample is then selected. The use of cluster sampling is supported by Cochran (1977), who argues that such an approach is efficient and appropriate when the target population is widespread and cannot be easily accessed as a whole. Through this method, the research successfully acquired 120 respondents, which is an adequate sample size for statistical estimation using SEM-PLS techniques and aligns with recommendations for multivariate analysis.

The primary data were obtained through an online questionnaire using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). The questionnaire contained items grouped into four constructs: *Career Self-Efficacy*, *AI Literacy*, *AI Attitude*, and *Job Seeking Anxiety*. Each construct was operationalized based on theoretical definitions and previous empirical studies compiled in the literature review section. For instance, *Career Self-Efficacy* was assessed through indicators including self-assessment, information seeking, goal formulation, career planning, and barrier coping behaviors. *Job Seeking Anxiety* items measured concerns about interview performance, employment uncertainty, emotional pressure, and external socio-economic demands. *AI Attitude* included beliefs regarding the benefits and risks of AI, willingness to adopt the technology, and trust in AI-generated recommendations. Finally, *AI Literacy* involved conceptual understanding, practical application skills, awareness of ethical implications, and ability to evaluate AI limitations.

Secondary data were drawn from scholarly journals, books, governmental publications, institutional reports, and previous theses and dissertations. These sources supported the construction of the theoretical framework and contextualized the findings relative to existing literature (Blumberg et al., 2014). The integration of secondary data helped reinforce the conceptual model and provided comparative insights regarding patterns identified in international and national studies.

The data collection procedure began with the distribution of the online questionnaire through university networks, academic groups, and digital communication channels commonly used by students. Participation was voluntary and responses were anonymized to promote honesty and reduce potential response bias. After data collection, the dataset was screened for completeness, consistency, and accuracy. Responses with missing or patterned answers were removed to ensure high-quality input for further analysis.

Before proceeding to hypothesis testing, rigorous instrument evaluation was conducted. Validity testing involved evaluating *convergent validity* through factor loadings and *Average Variance Extracted* (AVE). According to Hair et al. (2019), factor loadings must exceed 0.70 and AVE should be greater than 0.50 to indicate adequate convergent validity—criteria that were fulfilled by all constructs in the instrument. Reliability testing was performed using Cronbach's Alpha and Composite Reliability, with values above 0.70 considered satisfactory indicators of internal consistency. All constructs demonstrated reliability values exceeding these thresholds, confirming the robustness of the instrument.

The data analysis technique used in this study was *Structural Equation Modeling* with the *Partial Least Squares* approach (SEM-PLS), executed using SmartPLS 4.0 software. SEM-PLS was chosen because it is particularly suited for predictive and explanatory research involving complex models with mediators, does not require data normality, and is appropriate for moderate sample sizes. SEM-PLS consists of two evaluation stages: the outer-model assessment and the inner-model assessment. The outer-model assessment evaluated validity and reliability of constructs, while the inner-model assessment analyzed the strength and statistical significance of relationships among variables, including the effects of mediation.

The inner-model evaluation included computation of R^2 values to determine the explanatory power of the model. For example, *Career Self-Efficacy* explained 22.4% of the variance in *Job Seeking Anxiety*, placing it in the moderate explanatory range based on Hair et al. (2019) categorization. Path coefficients were then assessed to examine direct effects, with significance determined by bootstrapping procedures using 5,000 subsamples. Relationships were considered significant when p-values were below 0.05 and t-statistics exceeded 1.96. Indirect effects were tested to determine whether *AI Literacy* or *AI Attitude* served as mediators. These mediating effects were interpreted using criteria for full, partial, or no mediation as outlined by established SEM guidelines.

In summary, this methodological framework ensures a comprehensive, rigorous, and theoretically grounded examination of the relationships among psychological readiness, technological competence, and employment-related anxiety in the era of rapid AI expansion. By integrating robust sampling, validated instruments, and advanced statistical modeling, the study provides reliable evidence on how final-year students perceive and respond to emerging digital transformations in the labor market.

RESULT AND DISCUSSION

The analysis proceeded in two stages. First, the measurement model was assessed to verify that all indicators adequately captured their latent constructs; second, the structural model was tested to estimate the magnitude and direction of relations among variables and to evaluate the hypothesized mediations. Consistent with standard PLS-SEM practice outlined in the method section, convergent validity, internal consistency reliability, and explanatory power were examined before interpreting path coefficients and indirect effects.

Measurement model.

Convergent validity was supported across all constructs: the *Average Variance Extracted* (AVE) exceeded 0.50 for *Career Self-Efficacy* (0.636), *Job-Seeking Anxiety* (0.710), *AI Literacy* (0.649), and *AI Attitude* (0.652), indicating that each latent variable explained more than half of the variance in its indicators. Outer loadings mostly met or surpassed the recommended ≥ 0.70 threshold (e.g., *Career Self-Efficacy* 0.727–0.829; *Job-Seeking Anxiety* 0.816–0.871; *AI Literacy* 0.728–0.852; *AI Attitude* 0.740–0.844), further attesting to indicator quality. Internal consistency reliability was also satisfactory to high, with Cronbach's alpha and Composite Reliability values above 0.70 for all constructs (α/CR: *Career Self-Efficacy* 0.862/0.897; *Job-Seeking Anxiety* 0.898/0.924; *AI Literacy* 0.865/0.902; *AI Attitude* 0.867/0.903). Together, these indices indicate a robust measurement model, suitable for testing the structural relations posited in the research framework.

Table 1. Summary of Measurement Model

Construct	AVE	Example Outer Loadings	α	CR
Career Self-Efficacy	0.636	0.727–0.829	0.862	0.897
Job-Seeking Anxiety	0.710	0.816–0.871	0.898	0.924
AI Literacy	0.649	0.728–0.852	0.865	0.902
AI Attitude	0.652	0.740–0.844	0.867	0.903

Structural model and explained variance.

Having established measurement quality, the structural model was estimated using bootstrapping in SmartPLS. The model accounts for a meaningful portion of variance in *Job-Seeking Anxiety* (R^2 = 0.244; adjusted R^2 = 0.224), which falls in the low-to-moderate range for behavioral research involving psychological and technology-related constructs. This level of explanatory power suggests that while the included predictors are consequential, additional factors—such as social support, perceived job market uncertainty, work experience, or economic conditions—likely contribute to anxiety and may be considered in future models to improve coverage.

The pattern of direct effects shows a coherent and theoretically sensible structure. *Career Self-Efficacy* exhibits the largest standardized effect on *Job-Seeking Anxiety* ($\beta = -0.298$, $p = 0.001$), followed by *AI Attitude* ($\beta = -0.276$, $p = 0.000$) and *AI Literacy* ($\beta = -0.256$, $p = 0.013$). The negative signs indicate that increases in efficacy, positive attitudes to AI, and literacy are each associated with reductions in anxiety related to the job search process. In practical terms, the relative magnitudes imply that strengthening students' confidence in performing key career tasks (self-assessment, information seeking, planning, barrier management) yields the largest anxiety reduction among the three levers considered, with complementary benefits from cultivating constructive appraisals of AI and enhancing practical competencies to use AI-enabled tools in the search and application workflow.

Table 2. Direct Effects on Job-Seeking Anxiety

Path	Coefficient (β)	p-value	Interpretation
Career Self-Efficacy → Job-Seeking Anxiety	−0.298	0.001	Significant
AI Attitude → Job-Seeking Anxiety	−0.276	0.000	Significant
AI Literacy → Job-Seeking Anxiety	−0.256	0.013	Significant

Mediation tests.

Specific indirect effects were not statistically significant for any of the proposed mediation routes. The path *Career Self-Efficacy → AI Literacy → Job-Seeking Anxiety* yielded an indirect coefficient of 0.013 ($p = 0.712$), *Career Self-Efficacy → AI Attitude → Job-Seeking Anxiety* yielded −0.023 ($p = 0.478$), and the sequential chain *Career Self-Efficacy → AI Attitude → AI Literacy → Job-Seeking Anxiety* yielded 0.001 ($p = 0.924$). These results indicate that the anxiety-reducing influence of *Career Self-Efficacy* operated directly, not through the proposed attitudinal or literacy pathways in this sample.

Table 3. Specific Indirect (Mediation) Effects

Indirect Path	Indirect β	p-value
CSE → AIL → JSA	0.013	0.712
CSE → AIA → JSA	−0.023	0.478
CSE → AIA → AIL → JSA	0.001	0.924

For completeness, a compact model summary is provided below.

Table 4. Model Summary and Explained Variance

Endogenous Variable	R^2	R^2 Adjusted	Notes
Job-Seeking Anxiety	0.244	0.224	Low-to-moderate explanatory power

Interpretation and theoretical positioning.

The significance and direction of the three direct paths are consistent with the study's theoretical scaffolding. The *social-cognitive* view holds that efficacy beliefs shape emotional regulation and active coping during challenging tasks; in a job-search context, stronger *Career Self-Efficacy* should therefore dampen anxiety—a pattern observed here with the largest absolute standardized effect among predictors. Concurrently, technology-acceptance perspectives and digital/AI-literacy frameworks argue that seeing a technology as useful and feeling competent to use it reduces apprehension and increases perceived control; the significant negative paths from *AI Attitude* and *AI Literacy* to *Job-Seeking Anxiety* are in line with this logic. The absence of mediation suggests that, within this cohort and period, efficacy and AI-related competencies function more as parallel drivers than as sequential mechanisms channelling one into the other.

Several contextual features can help explain why mediation did not materialize despite robust direct effects. As noted in the manuscript's narrative, campus-level career services and digital/AI literacy initiatives are often delivered in parallel tracks rather than as an integrated curriculum. Under such arrangements, a student may develop high career efficacy through mentorship, internships, or career planning workshops, independently of their acquisition of AI-related skills or attitudes; conversely, exposure to AI tools in coursework may elevate literacy and acceptance without substantively transforming one's broader sense of career capability. In such scenarios, each factor directly reduces anxiety by its **own** mechanism—efficacy via emotional regulation and task mastery; literacy and attitude via perceived control over AI-enabled search, screening, and preparation—without forming a consistent chain from efficacy → attitude/literacy → anxiety.

Answering the research problems and hypotheses.

The findings allow clear answers to the guiding questions set out in the objectives: *(i) Career Self-Efficacy* significantly and negatively affects *Job-Seeking Anxiety*, supporting H1; *(ii) AI Literacy* and *AI Attitude* do **not** mediate the *Career Self-Efficacy → Job-Seeking Anxiety* relation, so H4–H6 are not supported; *(iii)* both *AI Literacy* and *AI Attitude* independently and significantly reduce *Job-Seeking Anxiety*, supporting H2 and H3. The hierarchy of standardized coefficients ($|\beta|$: 0.298 > 0.276 > 0.256) further indicates that, among levers included in the model, efficacy is the strongest single predictor of lower anxiety, with attitude and literacy providing meaningful, additive benefits.

Implications for practice.

The joint pattern of results motivates a three-pillar intervention strategy for university career centers and faculties. First, intensify *efficacy-building* modules (self-assessment, goal setting, barrier-coping drills, interview simulations) to address the largest lever observed. Second, cultivate *constructive AI attitudes* by demystifying recruitment technologies (e.g., ATS parsing, AI-assisted résumé feedback, interview bots), clarifying benefits and limitations, and aligning expectations. Third, extend *AI literacy* through hands-on training with job-search-relevant tools—ATS checkers, job-matching platforms, and AI-supported mock interviews—so students gain practical fluency that translates into lower anxiety. Delivering these pillars together rather than in isolation should exploit the additive nature of the direct effects observed in this model.

Methodological notes and robustness.

The outer-model diagnostics (AVE and loadings) and reliability indices (α and CR) exceeded conventional thresholds, lending confidence to construct measurement. The inner-model evaluation used bootstrapping to derive p-values, and the interpretation of R^2 placed the model in a credible though improvable range of explanatory power. While additional statistics (e.g., effect sizes f^2, predictive relevance Q^2, multicollinearity checks) were not reported in the results provided, the combination of significant direct paths and non-significant indirect paths yields a coherent narrative consistent with the theorized roles of efficacy and technology-related competencies. Future work that augments the present model with social and market variables—and that integrates curricular interventions more tightly—may help raise explained variance and test whether mediation emerges under integrated program designs.

In sum, the study demonstrates that psychological readiness and technology-related readiness each matter for alleviating students' anxiety during the transition to work in the era of *Artificial Intelligence*. Strengthening *Career Self-Efficacy* remains the most powerful single lever, while fostering *AI Attitude* and *AI Literacy* provides additional, independent relief. The absence of mediation cautions against assuming that one domain will automatically translate into the other; rather, programs should build both deliberately to realize the full spectrum of benefits identified by the model.

CONCLUSION

Anchored to the study's title—The Influence of Career Self-Efficacy on Job Seeking Anxiety: The Mediating Role of AI Attitude and AI Literacy among Final-Year University Students—the findings demonstrate that confidence in performing career tasks consistently lowers anxiety during the job search, while positive appraisals of, and literate engagement with, Artificial Intelligence further reduce that anxiety through direct pathways. These conclusions answer the research objectives by confirming a significant negative effect of Career Self-Efficacy on Job-Seeking Anxiety, establishing independent, significant contributions of AI Attitude and AI Literacy to anxiety reduction, and rejecting the proposed single and chain mediations; taken together, the results indicate that psychological readiness and technology-related readiness act as parallel levers rather than sequential mechanisms in this cohort.

Methodologically, the measurement model satisfied accepted thresholds for convergent validity and reliability, and the structural model explained a meaningful, if moderate, share of variance in Job-Seeking Anxiety, thereby supporting inferences that are proportionate to the observed effects and free of claims not borne out by the data. Within these bounds, the study improves the applied knowledge base for industrial engineering and the broader sciences of work and organizations by clarifying where interventions are likely to yield the greatest marginal gains: designing integrated career-readiness programs that explicitly cultivate Career Self-Efficacy while, in parallel, building realistic, constructive attitudes toward AI and practical literacy with recruitment-relevant tools. Such evidence helps inform the engineering of human–technology systems in talent pipelines—curriculum design, capability building, and AI-enabled recruitment support—so that anxiety is mitigated through deliberate alignment of human factors and technological affordances. Future research can extend explanatory power by incorporating social and market variables, but the present conclusions remain directly tied to the tested model and its statistically supported relations.

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