The Influence of Personal and Social Resources on Career Adaptability among Chinese Engineering Undergraduates

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Abstract

Career adaptability is increasingly important for university students navigating rapid labor-market and technological change. This study examined the predictive relationships of self-leadership, self-efficacy, cognitive flexibility, AI literacy, and social support with career adaptability among Chinese engineering undergraduates. Drawing on Career Construction Theory and Social Cognitive Theory, the study adopted a cross-sectional quantitative design. Using stratified random sampling, self-reported questionnaire data were collected from 416 junior and senior students in the College of Civil Engineering at a comprehensive university in Guangxi, China. Pearson correlation analysis and multiple regression analysis were employed to examine bivariate associations and the unique contribution of each predictor. All five resources were positively correlated with career adaptability ($p < .001$). In the five-predictor regression model, self-leadership ($\beta = .394$) and cognitive flexibility ($\beta = .276$) showed comparatively stronger predictive relationships, followed by self-efficacy ($\beta = .130$), AI literacy ($\beta = .126$), and social support ($\beta = .072$). The model explained 75.9% of the variance in career adaptability (adjusted $R^2 = .756$). These findings suggest that self-regulatory, cognitive, technological, and relational resources each made a unique statistical contribution within the present sample. The comparatively larger coefficients for self-leadership and cognitive flexibility may help universities calibrate the emphasis of career-development programs while continuing to support students' efficacy beliefs, AI literacy, and social networks. Educational initiatives may therefore combine goal setting, self-monitoring, flexible problem solving, critical and ethical use of AI tools, and accessible mentoring or peer support. The study also extends career-adaptability research to engineering undergraduates in inland China. Given the cross-sectional and self-reported nature of the data, the findings should be interpreted as predictive associations rather than causal effects, and the high explained variance warrants cautious interpretation.

Keywords: career adaptability; self-leadership; cognitive flexibility; ai literacy; engineering undergraduates

Introduction

Contemporary occupational landscapes are undergoing rapid transformation driven by globalization, digitalization, and the proliferation of artificial intelligence (Johnston, 2018; Sullivan & Baruch, 2009). In China, higher education has experienced substantial expansion, with approximately 11.7 million graduates in 2024 (Ministry of Education of the People's Republic of China, 2025). At the same time, emerging technologies are reshaping occupational structures, with projections suggesting that many work activities may be substantially transformed by AI between 2030 and 2060 (Chui et al., 2023). For engineering undergraduates facing intensified labor–market competition and changing technical work, developing career adaptability is therefore particularly important.

Career adaptability, defined as the psychosocial readiness and resources individuals use to address vocational tasks, transitions, and disruptions (Savickas, 2005), has become a central construct in vocational psychology. Prior research has linked it with employment outcomes, well–being, and career success (Akkermans et al., 2018; Guan et al., 2013), but studies have often examined psychological resources, social resources, or technological competencies separately. Few have compared the independent predictive roles of established personal resources, contextual support, and AI literacy within one framework, particularly among engineering students in inland China. The theoretical value of integrating AI literacy lies not merely in its novelty, but in its representation of a technology–specific resource that may complement established psychological and social resources in responding to AI–related occupational change.

To address this gap, the present study focuses on engineering students in Guangxi, an inland province whose industrial and educational context differs from that of major coastal regions. Career Construction Theory explains career adaptability as an adaptive psychosocial resource, whereas Social Cognitive Theory helps explain how personal beliefs, self–regulatory capacities, and contextual support are associated with adaptive career behavior. The study therefore examines the collective and relative predictive contributions of self–leadership, self–efficacy, cognitive flexibility, AI literacy, and social support without changing the proposed variables or relationships.

Research Objective

In summary, this paper examines how personal, technological, and social resources are associated with career adaptability among Chinese engineering undergraduates. The specific research objectives are as follows:

1. To examine the bivariate relationships between self–leadership, self–efficacy, cognitive flexibility, AI literacy, social support, and career adaptability among Chinese engineering undergraduates.

2. To estimate the unique predictive relationship of each factor with career adaptability while the other predictors are held constant.

Literature Review

Career Adaptability

Savickas (2005) conceptualized career adaptability as a multifaceted psychosocial resource comprising four interrelated dimensions: concern (future–oriented planning), control (self–regulation and responsibility), curiosity (exploratory behaviors), and confidence (problem–solving self–assurance). This construct represents an evolution from earlier notions of career maturity, emphasizing dynamic person–environment transactions rather than static developmental milestones.

Empirical investigations have consistently demonstrated that career adaptability facilitates positive vocational outcomes, including enhanced job search efficacy, organizational socialization, and career satisfaction (Guan et al., 2013; Maggiori et al., 2013). Nevertheless, the antecedents of career adaptability—particularly the interplay between cognitive, volitional, and social resources—remain inadequately explicated, especially among applied science students confronting rapid technological shifts.

Self–Leadership and Career Adaptability

Self–leadership denotes a self–influence process through which individuals employ behavioral and cognitive strategies to achieve self–direction and intrinsic motivation (Neck & Houghton, 2006). This construct encompasses three strategic domains: behavior–focused strategies (e.g., goal setting, self–monitoring), natural reward strategies (e.g., incorporating intrinsically enjoyable elements into tasks), and constructive thought pattern strategies (e.g., positive self–talk, mental rehearsal). The nexus between self–leadership and career adaptability is theoretically grounded in agency theory: individuals who proactively govern their actions are better positioned to navigate career uncertainties. Empirical support derives from Megheirkouni (2018) and Bao et al. (2025), who documented positive associations between self–leadership and career development outcomes across diverse occupational contexts.

Self–Efficacy and Career Adaptability

Grounded in Bandura's (1986, 1997) social cognitive theory, self–efficacy denotes the conviction that one can successfully execute actions requisite for achieving desired outcomes. Within vocational domains, self–efficacy influences career–related choices, effort investment, and persistence in the face of obstacles. Bubic (2017) demonstrated that career decision–making self–efficacy serves as a core psychological resource that fosters career optimism and adaptability. Similarly, Chuang et al. (2022) empirically validated self–efficacy's role in enhancing career adaptability among vocational students, with its effects mediated through diminished fear of failure and strengthened goal–directed behaviors. These findings suggest that efficacy beliefs constitute foundational psychological endowments enabling proactive career management.

Cognitive Flexibility and Career Adaptability

Cognitive flexibility refers to the capacity to restructure one's knowledge and shift cognitive sets in response to changing environmental demands (Dennis & Vander Wal, 2010). This attribute encompasses three components: perceiving difficult situations as controllable, generating multiple alternative explanations for events, and developing diverse solutions to problems. Within career construction theory, adaptive behavior necessitates cognitive flexibility to effectively negotiate occupational transitions (Savickas & Porfeli, 2012). Empirical studies corroborate this assertion: Yıldız–Akyol and Boyacı (2020) found that cognitive flexibility positively predicts career future scores among university students, while Demirtaş and Kara (2022) identified it as a critical predictor of adaptive capacities in emerging adults.

AI Literacy and Career Adaptability

AI literacy comprises the competencies required to critically evaluate, collaborate with, and apply artificial intelligence technologies across work, learning, and daily life contexts (Long & Magerko, 2020). As AI permeates professional domains, this literacy has transitioned from an optional technical skill to an essential occupational competency (Černý, 2024; Cetindamar et al., 2024). Kong et al. (2021) demonstrated that AI literacy promotes career development by enabling effective utilization of technological tools and fostering innovation. Tang et al. (2025) further established that students possessing robust AI literacy can more effectively adapt to AI–driven occupational transformations, while Mohsin et al. (2025) reported that perceived AI competency enhances career optimism and strategic career planning.

Social Support and Career Adaptability

Social support encompasses the perceived availability of assistance from one's social network, including family, friends, and significant others (Zimet et al., 1988). This resource functions both instrumentally (e.g., providing tangible aid, information, guidance) and emotionally (e.g., offering encouragement, validation). Kenny and Bledsoe (2005) found that social support enhances career adaptability among urban adolescents by buffering environmental risks and reinforcing vocational exploration. Hirschi et al. (2011) similarly demonstrated that support from multiple sources indirectly improves career decision quality through strengthened career engagement behaviors. Meta–analytic evidence (Stead et al., 2025) confirms a significant positive, albeit modest, association between social support and career adaptability, underscoring its complementary role alongside internal psychological resources.

The five predictors represent conceptually different resources. Self–leadership concerns the active use of behavioral and cognitive self–regulation strategies, whereas self–efficacy concerns individuals' beliefs about their ability to perform required actions. Cognitive flexibility concerns the adjustment of thinking and problem–solving strategies when circumstances change. AI literacy represents a context–specific capacity to understand, use, and critically evaluate AI–related tools,

which is particularly relevant because engineering students are likely to encounter AI–supported technologies and changing technical work processes. Social support, by contrast, represents an external relational resource that may operate differently from internal personal resources. These distinctions justify comparing the five predictors in one model without presuming in advance which will show the largest coefficient.

Conceptual Framework

The theoretical framework integrates Career Construction Theory (Savickas, 2005; Rossier, 2015) and Social Cognitive Theory (Bandura, 1986). Career Construction Theory provides the principal explanation of career adaptability as a psychosocial resource expressed through concern, control, curiosity, and confidence. Social Cognitive Theory complements this account by explaining how efficacy beliefs, self–regulatory capacities, behavior, and social–environmental conditions are associated with adaptive action.

Together, the two theories support an analysis that includes personal and contextual resources. Self–leadership represents active self–regulation, self–efficacy represents beliefs about capability, cognitive flexibility represents adaptive thinking, AI literacy represents a contemporary technology–specific resource, and social support represents relational context. Their integration permits a comparison of unique predictive relationships while retaining career adaptability as the focal outcome.

Existing studies have established separate relationships between these resources and career–development outcomes. However, limited research has simultaneously compared their unique predictive relationships with career adaptability, particularly by incorporating AI literacy and focusing on engineering undergraduates in inland China.

Based on this integrative theoretical synthesis and the empirical evidence reviewed, the following hypotheses were formulated:

H 1: Self–leadership exerts a significant positive effect on career adaptability.

H2: Self–efficacy exerts a significant positive effect on career adaptability.

H3: Cognitive flexibility exerts a significant positive effect on career adaptability.

H4: AI literacy exerts a significant positive effect on career adaptability.

H5: Social support exerts a significant positive effect on career adaptability.

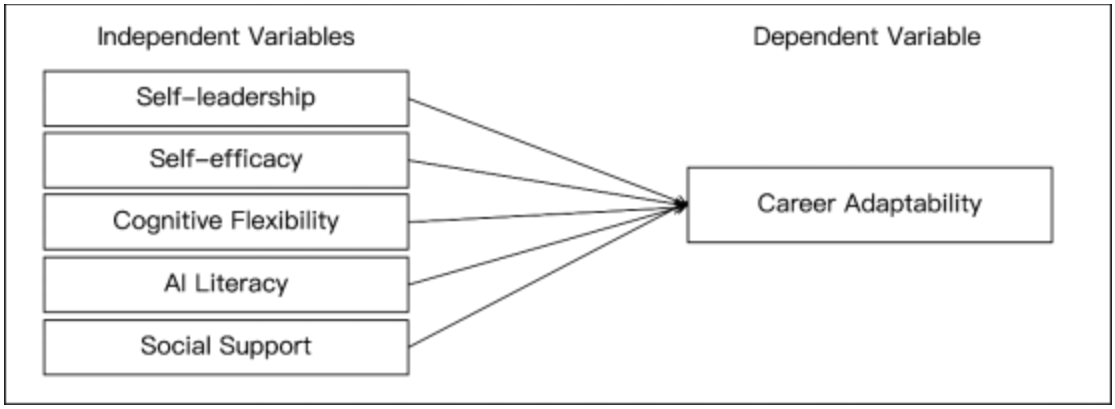


Figure 1 Conceptual Framework of the Study

Research Methodology

Research Design, Population, and Sampling

This study adopted a cross-sectional quantitative survey design. The target population comprised 1,026 junior and senior undergraduate students enrolled in the College of Civil Engineering at a comprehensive university in Guangxi, China, including 532 junior students and 494 senior students. The achieved analytical sample comprised 416 students, exceeding the minimum recommendation in Krejcie and Morgan's (1970) sample-size table.

A stratified random sampling method was used, with grade as the stratification variable. Students were selected proportionately within the junior and senior strata using computer-generated random numbers and were contacted through class group chats with individually assigned questionnaire codes. Data were collected from April to May 2026; completion required approximately 15–20 minutes. Of 449 returned questionnaires, 33 were excluded: 15 contained more than 10% missing responses, 9 were completed in less than one-third of the sample median time, and 9 showed invariant or obvious patterned responses. The final sample comprised 216 junior and 200 senior students (N = 416).

Ethical approval was obtained from the Institutional Research Ethics Committee of the participating university (approval No. IRB-2026-041). Participation was voluntary, informed consent was obtained before questionnaire completion, responses were collected anonymously, and students were informed that they could withdraw at any time without penalty.

Measures

All constructs were operationalized using established instruments adapted to the Chinese engineering-student context. Responses were recorded on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Three experts in career education, educational psychology, and educational measurement evaluated content validity, and all items achieved an Item-Objective Congruence (IOC) index above 0.50. A pilot test with 51 students who were not included in the final analytical sample indicated high internal consistency across the subscales. Table 1 presents the

reliability and validity information for the Career Adaptability and Factors Affecting Career Adaptability Questionnaire (CAFAQ).

Table 1 Reliability and Validity of the CAFAQ

Variable Scale	N of Items	IOC	Cronbach's Alpha	CITC
Career adaptability	16	0.938	0.952	0.517–0.845
Self–leadership	13	0.904	0.939	0.532–0.848
Self–efficacy	9	0.889	0.942	0.646–0.852
Cognitive flexibility	6	0.708	0.927	0.610–0.884
AI literacy	12	0.944	0.929	0.604–0.769
Social support	12	0.972	0.958	0.717–0.879
Overall	**68**		**0.986**	

Career adaptability was assessed with 16 items from the Career Adapt–Abilities Scale–International Form 2.0 (Savickas & Porfeli, 2012). Self–leadership was measured with 13 items from the Revised Self–Leadership Questionnaire (Houghton & Neck, 2002); self–efficacy with 9 items from the General Self–Efficacy Scale (Schwarzer & Jerusalem, 1995); cognitive flexibility with 6 items from the Cognitive Flexibility Inventory (Dennis & Vander Wal, 2010); AI literacy with 12 items from the Artificial Intelligence Literacy Scale (Wang et al., 2023); and social support with 12 items from the Multidimensional Scale of Perceived Social Support (Zimet et al., 1988).

The English–language measures were translated independently into Chinese by two bilingual researchers and back–translated by a third bilingual researcher who had not seen the source wording. Translation differences were resolved jointly, and three subject–matter experts reviewed semantic equivalence and relevance to Chinese engineering undergraduates. To reduce redundancy and response burden while retaining construct coverage, the adapted questionnaire retained 16 of the 24 Career Adapt–Abilities Scale items (four each for concern, control, curiosity, and confidence), 13 of the 35 Revised Self–Leadership Questionnaire items across behavior–focused, natural–reward, and constructive–thought strategies, 9 of the 10 General Self–Efficacy Scale items, and 6 of the 20 Cognitive Flexibility Inventory items representing Alternatives and Control. All 12 AI Literacy Scale items and all 12 Multidimensional Scale of Perceived Social Support items were retained. Minor contextual wording changes referred to academic and career situations faced by engineering undergraduates; items were removed only when experts judged them redundant or insufficiently relevant, and all retained items showed corrected item–total correlations above .50 in the pilot test.

Data Analysis

Descriptive statistics, Pearson correlations, Harman's single–factor test, and multiple regression were conducted in IBM SPSS Statistics 27.0. All five predictors were entered simultaneously using the Enter method; tolerance and variance inflation factor (VIF) values were

examined for multicollinearity. A correlated six–factor confirmatory factor analysis was estimated with maximum likelihood in IBM SPSS AMOS 26.0. Measurement quality was assessed using standardized factor loadings, composite reliability (CR), average variance extracted (AVE), and the Fornell–Larcker criterion. Model fit was evaluated with χ^2/df, CFI, TLI, RMSEA, and SRMR.

Procedural controls for common method bias included anonymous participation, voluntary participation, protection of identifying information, neutral instructions emphasizing that there were no right or wrong answers, and separation of construct sections in the questionnaire. Harman's single–factor test was used as a diagnostic check; because this procedure is limited, its result was interpreted as an indication rather than definitive evidence that common method bias was absent.

Research Results

Measurement Model Assessment

The correlated six–factor measurement model showed acceptable fit: $\chi^2(2195) = 5028.740$, $\chi^2/df = 2.291$, CFI = .912, TLI = .909, RMSEA = .056, and SRMR = .052. As shown in Table 2, standardized factor loadings ranged from .670 to .880. CR values ranged from .924 to .964, and AVE values ranged from .552 to .682, supporting internal consistency and convergent validity.

Table 2 Measurement Model Assessment

Construct	Factor–loading range	Cronbach's alpha	CR	AVE
Career adaptability	.750–.830	.952	.96	.62
Self–leadership	.720–.840	.939	.95	.61
Self–efficacy	.760–.850	.942	.94	.66
Cognitive flexibility	.780–.860	.927	.92	.67
AI literacy	.670–.800	.929	.94	.55
Social support	.770–.880	.958	.96	.68

Note. CR = composite reliability; AVE = average variance extracted. CR and AVE are rounded to two decimals; loading ranges report standardized estimates.

The Fornell–Larcker results are presented in Table 3. The square root of AVE exceeded the relevant interconstruct correlations for most comparisons. The criterion was not fully satisfied for the career adaptability–self–leadership pairing (r = .821) or the self–efficacy–cognitive flexibility pairing (r = .817), indicating partial empirical overlap among these closely related personal–resource constructs. The constructs were retained because they were theoretically distinct, had acceptable convergent validity, and showed VIF values below 5, but coefficients involving these variables should be interpreted cautiously.

Table 3 Fornell–Larcker Discriminant Validity Matrix

Variable	Y	X1	X2	X3	X4	X5
Y	.790					
X1	.821	.781				
X2	.759	.753	.809			
X3	.784	.752	.817	.819		
X4	.658	.672	.587	.570	.743	
X5	.521	.509	.460	.476	.460	.826

Note. Diagonal values are the square roots of AVE; off–diagonal values are construct correlations. All correlations are significant at $p < .001$.

Descriptive Statistics

As indicated in Table 4, the mean values for all variables ranged from 4.02 to 4.24, suggesting that participants reported medium–high to high levels across the constructs. Social support had the highest mean ($M = 4.24$, $SD = 0.51$), whereas self–efficacy had the lowest mean ($M = 4.02$, $SD = 0.51$). Career adaptability had a mean of 4.13 ($SD = 0.46$).

Table 4 Descriptive Statistics (N = 416)

Variable	N	Min	Max	M	SD	Level
Career Adaptability (Y)	416	1.00	5.00	4.13	0.46	Medium high level
Self–Leadership (X1)	416	1.00	5.00	4.18	0.43	Medium high level
Self–Efficacy (X2)	416	1.00	5.00	4.02	0.51	Medium high level
Cognitive Flexibility (X3)	416	1.00	5.00	4.05	0.53	Medium high level
AI Literacy (X4)	416	1.00	5.00	4.15	0.47	Medium high level
Social Support (X5)	416	1.00	5.00	4.24	0.51	High level

Correlation Analysis

Pearson correlations, presented in Table 5, showed that all five predictors were significantly and positively associated with career adaptability ($p < .001$). Self–leadership had the largest bivariate association with career adaptability ($r = .821$), followed by cognitive flexibility ($r = .784$), self–efficacy ($r = .759$), AI literacy ($r = .658$), and social support ($r = .521$). The relatively high correlation between cognitive flexibility and self–efficacy ($r = .817$) indicates substantial shared variance, consistent with the partial overlap identified in the Fornell–Larcker assessment; regression coefficients were therefore interpreted together with the multicollinearity diagnostics.

Table 5 Bivariate Correlation Matrix

Variable	Y	X1	X2	X3	X4	X5
Y	1					
X1	.821	1				
X2	.759	.753	1			
X3	.784	.752	.817	1		
X4	.658	.672	.587	.570	1	
X5	.521	.509	.460	.476	.460	1

Note. All correlations are significant at $p < .001$.

Common Method Bias Assessment

In the unrotated exploratory factor solution containing all 68 items, the first factor explained 38.7% of the total variance. Because this proportion was below 50%, common method bias was unlikely to account for the majority of the observed covariance. Nevertheless, the result does not exclude common method bias, particularly because all variables were measured by self–report at one time point.

Regression Analysis

Multiple regression analysis was conducted with all five predictors entered in the same model. The model explained a substantial proportion of the variance in career adaptability ($R = .871$, $R^2 = .759$, adjusted $R^2 = .756$; $F(5, 410) = 258.176$, $p < .001$). All five variables showed significant positive coefficients: self–leadership ($\beta = .394$, $p < .001$), cognitive flexibility ($\beta = .276$, $p < .001$), self–efficacy ($\beta = .130$, $p = .004$), AI literacy ($\beta = .126$, $p < .001$), and social support ($\beta = .072$, $p = .014$). Tolerance values ranged from .284 to .700 and VIF values from 1.428 to 3.516, indicating that multicollinearity did not exceed the conventional VIF threshold of 5. However, the high correlations and partial discriminant–validity overlap among several personal–resource variables indicate shared variance. The high explained variance should also be interpreted cautiously because all variables were measured through self–reported questionnaires at the same time.

$$\hat{Y} = 0.119 + 0.422X1 + 0.118X2 + 0.241X3 + 0.125X4 + 0.065X5$$

Table 6 Multiple Regression Coefficients

Model	B	SE	β	t	p	Tolerance	VIF
Constant	0.119	0.121		0.978	.329		
X1	0.422	0.047	.394	9.058	< .001	.311	3.219
X2	0.118	0.041	.130	2.873	.004	.284	3.516
X3	0.241	0.040	.276	6.084	< .001	.286	3.499
X4	0.125	0.033	.126	3.741	< .001	.518	1.930
X5	0.065	0.026	.072	2.473	.014	.700	1.428

Note. All five predictors were entered simultaneously. Tolerance and VIF values are reported for each predictor.

Discussion

The primary objective of this investigation was to estimate the predictive relationships of self–leadership, self–efficacy, cognitive flexibility, AI literacy, and social support with career adaptability among Chinese engineering undergraduates. All five resources were significantly associated with career adaptability in the reported model. Their standardized coefficients differed, but these differences should be interpreted as a sample–specific relative pattern of predictive associations rather than a hierarchy of causal influence.

Self–leadership showed the largest standardized regression coefficient in the present model (β = .394), consistent with the positive relationships reported by Park (2021) and Bao et al. (2025). Self–leadership involves goal setting, self–monitoring, natural–reward strategies, and constructive thought patterns, which conceptually align with the self–regulatory demands of career planning and transition management. Among engineering students facing changing technical work, the observed coefficient suggests that active self–direction may be particularly relevant, although the cross–sectional design does not establish that self–leadership causes greater career adaptability.

Cognitive flexibility showed the second–largest standardized coefficient (β = .276), aligning with Career Construction Theory (Savickas & Porfeli, 2012) and prior findings among university students (Demirtaş & Kara, 2022; Yıldız–Akyol & Boyacı, 2020). However, its high correlation with self–efficacy (r = .817) and the incomplete Fornell–Larcker separation for this pairing indicate considerable shared variance. Although both constructs retained acceptable convergent validity and VIF values below 5, the coefficient should be interpreted as a conditional association within the simultaneous model rather than proof that the constructs were fully independent in this sample.

Self–efficacy remained a significant predictor but had a smaller standardized coefficient (β = .130) than self–leadership and cognitive flexibility. This positive relationship is consistent with Social Cognitive Theory and prior evidence linking efficacy beliefs with career adaptability (Bubic, 2017; Chuang et al., 2022). One possible explanation for the smaller unique coefficient is that self–efficacy shared considerable variance with self–leadership and cognitive flexibility, leaving a more limited distinct contribution after the other predictors were controlled.

AI literacy showed a significant positive coefficient (β = .126), consistent with emerging evidence connecting AI–related competencies with career preparation and adaptability (Kong et al., 2021; Tang et al., 2025). AI literacy may involve understanding basic AI concepts, using AI–supported tools, critically evaluating AI outputs, and recognizing ethical implications. These capacities are relevant to engineering students because they are likely to encounter AI–supported tools and changing technical work processes. However, the present analysis used an overall AI–literacy score and did not distinguish the separate predictive relationships of specific AI–literacy dimensions.

Social support remained statistically significant but showed the smallest unique coefficient (β = .072) after the other predictors were controlled. The direction of this result is consistent with the positive overall association reported by Stead et al. (2025). It should not be interpreted as evidence that social support is unimportant, because its coefficient may be affected by shared variance, the simultaneous inclusion of several personal resources, and characteristics of the present sample.

Limitations

This study has four closely related limitations. First, the cross–sectional design cannot establish causal relationships. Second, self–reported questionnaires collected at one time point may be affected by common method bias. Third, the sample was drawn from junior and senior engineering students at one university in Guangxi, which limits generalizability. Future research may use longitudinal designs, multi–university samples, and data from multiple sources to test the robustness of the reported associations.

New Knowledge from Research

This study contributes theoretical and empirical evidence to the career–adaptability literature in three respects.

First, it provides preliminary evidence regarding the relative predictive strength of five resources in the present sample. Self–leadership and cognitive flexibility showed the two largest standardized coefficients, but this pattern is sample–specific and does not establish a universal taxonomy or causal ranking.

Second, the study extends the existing predictive framework by incorporating AI literacy as a contemporary technological resource. Its significant coefficient suggests that AI–related understanding and use may complement established psychological and social resources in career preparation.

Third, the study extends the empirical context of career–adaptability research to engineering undergraduates in Guangxi, an inland region that is less frequently represented in the literature.

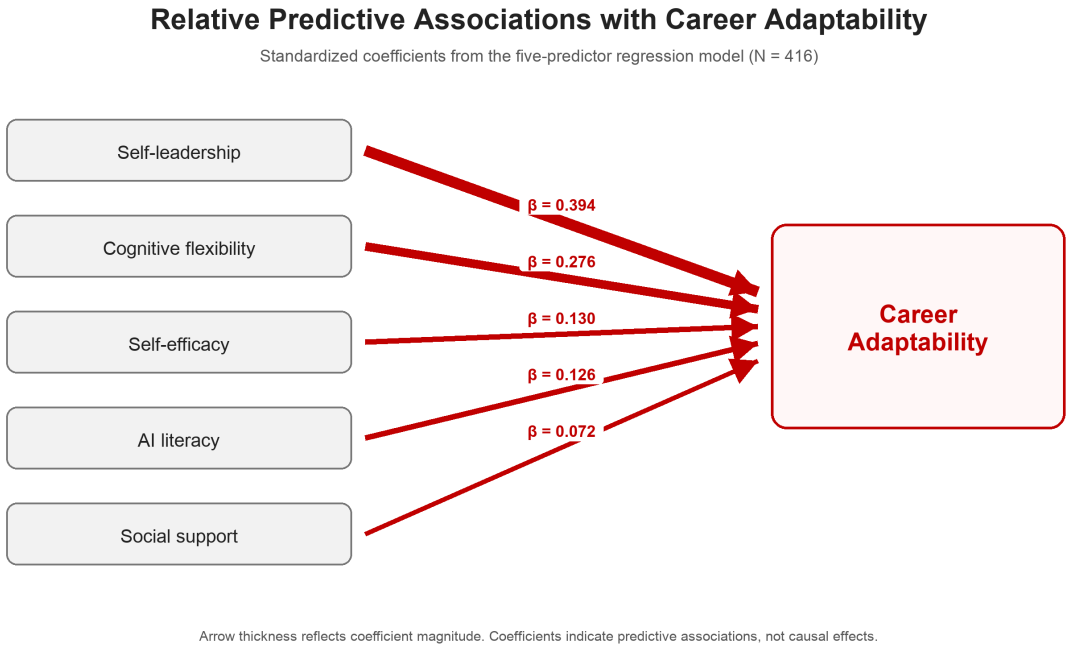


Figure 2 Relative Predictive Associations with Career Adaptability

Note. The coefficients indicate relative predictive associations based on cross-sectional data and should not be interpreted as causal effects.

Conclusion

This study examined the predictive relationships of self-leadership, self-efficacy, cognitive flexibility, AI literacy, and social support with career adaptability among Chinese engineering undergraduates. The findings indicate that all five variables were significant predictors in the reported model. Self-leadership and cognitive flexibility showed comparatively larger standardized coefficients, while AI literacy retained an independent positive coefficient. This relative pattern of predictive associations supports continued attention to personal, technological, and relational resources without implying a causal hierarchy of effects.

The study extends career-adaptability research by incorporating AI literacy and by focusing on engineering undergraduates in Guangxi. For educational practice, universities may consider combining self-leadership and cognitive-flexibility activities with efficacy-building experiences, AI-literacy education, and social-support systems. These conclusions are limited to cross-sectional, self-reported data obtained from junior and senior engineering students at one university in Guangxi and should not be interpreted as evidence of causal effects.

Suggestions

Based on the reported associations, the following recommendations are offered for students and higher education institutions:

For individual students: Engineering undergraduates may cultivate self–leadership through clear academic and career goals, progress monitoring, and constructive self–reflection. They may strengthen cognitive flexibility by engaging with interdisciplinary problems and generating alternative solutions, and build self–efficacy through incremental mastery experiences and feedback. AI–literacy development may extend beyond basic tool use to include critical evaluation of outputs and ethical awareness. Students may also maintain supportive social networks during demanding career transitions.

For universities: Career–guidance curricula may consider prioritizing self–leadership activities and problem–based learning that promotes flexible thinking, while also providing efficacy–building experiences. Universities may integrate AI literacy into general education so that students understand the use, evaluation, and ethical implications of AI. Mentoring, peer–support, and alumni–engagement programs may continue to provide complementary relational resources.

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