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Transformational leadership and future work readiness among Chinese vocational college students: AI literacy and career self-regulation as dual mediators

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Amid accelerating digital transformation, students in vocational colleges face increasing uncertainty about their future career prospects. Grounded in the Cognitive Appraisal Theory (CAT) and Social Cognitive Career Theory (SCCT), this study proposed and tested a dual-path mediation model in which transformational leadership (TL) in educational settings influenced students' future work readiness (FWR) through two mechanisms: AI literacy and career self-regulation (career control and decision-making difficulties) factors. The structural equation modeling and bootstrapped mediation analyses using data from 697 Chinese vocational college students revealed that TL indirectly enhanced career optimism and reduced future work anxiety through these mediators. Taken together, the findings are consistent with a full-mediation account: indirect effects were significant, and the direct links from TL to CO and to FWA attenuated to non-significance once the mediators were included. The findings positioned AI literacy as a critical cognitive bridge linking educational leadership to vocational psychological outcomes, and extended theoretical models of future work readiness and psychological adaptation to digitally evolving educational contexts.

KEYWORDS

transformational leadership, AI literacy, future work readiness, vocational education, structural equation modeling

1 Introduction

Driven by the rapid advancement of artificial intelligence (AI), big data, and automation technologies, the global employment landscape is undergoing profound and unprecedented transformations (Green, 2024; OECD, 2021). The World Economic Forum (2023) projects that over 50% of current vocational skills will require restructuring by 2030. In this context, essential attributes such as technical adaptability, interdisciplinary thinking, and psychological resilience have become critical indicators of future employability across both developed and emerging economies (Honorati et al., 2024).

As the main demographic preparing to transition into the workforce, vocational college students' future work readiness (FWR) has become a topic of growing interest among international scholars and policymakers. While the concept has been studied in diverse cultural settings, students across the globe—including those in Asia, Europe, and Latin America—consistently face challenges such as ambiguous career goals, decision-making difficulties, and elevated career-related anxiety, highlighting the universal nature of psychological readiness for future employment (Ahmid et al., 2023).

Although this study was conducted within China's vocational college system, the issues it addressed—such as future work anxiety, digital readiness, and psychological control—are increasingly relevant across global contexts. Vocational education systems across the globe similarly face challenges in cultivating students' adaptability to automation and digitally disrupted labor markets (OECD, 2021). This research may give culturally grounded insights to support policy and pedagogical improvements in other comparable national vocational training systems experiencing a digital revolution.

Future work readiness (FWR) is the combination of cognitive preparedness and emotional responses (e.g., career optimism, an individual's positive expectations for future career development; future work anxiety, anticipatory distress caused by uncertainty about future employment) when faced with dynamic and uncertain career trajectories. FWR, a new concept in global career psychology, emphasizes flexibility and emotional stability throughout labor market shifts (Jia et al., 2022). Self-efficacy and social support have been studied, but there are no integrated theoretical models that explain how educational interventions—particularly teacher leadership—can affect students' vocational psychological resources. It is particularly true in vocational education systems, which are modernizing in many countries but lack appropriate research on the psychological effects of educational leadership.

Transformational leadership (TL), which emphasizes visionary motivation, individualized support, intellectual stimulation, and idealized influence, has been shown to improve personal and professional development in organizations and schools (Bass and Avolio, 1996; Maduforo et al., 2024). These four characteristics enable leaders to inspire followers, meet their needs, question conventional thinking, and exhibit exceptional values and actions. Teachers are becoming informal leaders who can shape students' adaptation and competency in the face of fast-changing technology demands, including AI integration.

AI literacy is a key 21st-century skill for worldwide employment. AI literacy is the ability to critically evaluate, apply, and ethically interact with AI systems, spanning across cultures and economies (Çoban, 2025; Shelton, 2024). Higher AI literacy is associated with better professional autonomy, fewer decision-making challenges, and improved optimism and lower concern about future work (Er and Demirbilek, 2023).

To address these theoretical gaps, the present study proposes and validates a dual-path mediation model grounded in the Cognitive Appraisal Theory and Social Cognitive Career Theory, which jointly explain the cognitive and psychological mechanisms influencing students' future work readiness. Within this integrative framework, perceived teachers' transformational leadership is hypothesized to foster students' AI literacy (a cognitive resource), which in turn influences their career control (positive psychological resource) and decision-making difficulties (negative psychological resource). These mediating factors should influence students' future work preparedness, defined as career optimism and decreased work anxiety.

This research adds a culturally grounded perspective to career preparedness literature by employing a multi-theoretical framework and evaluating data from Chinese vocational college students, a sector experiencing fast restructuring to meet global skill objectives. The results seek to influence local educational practice and cross-national debates on how leadership, cognitive resources, and psychological adaptability enhance young people's professional prospects in the AI age. These results may apply to other locations with education–labor transition issues, especially those investing in vocational digital literacy.

2 Literature review and hypotheses development

2.1 Transformational leadership and AI literacy

Educational leadership is increasingly important in developing students' future-oriented skills in the context of fast digital economic development and AI. Transformational Leadership (TL)—vision articulation, intellectual stimulation, customized assistance, and role modeling—is known to boost motivation, self-efficacy, and growth (Paladhi and Maruthaveeran, 2024; Sacavém et al., 2025). TL increases technology acceptability, innovation, and digital transformation adaptation in organisations (Subroto et al., 2024). TL improves pupils' mental health and learning. For instance, a study in Vocational High Schools found that teacher TL significantly enhanced students' perceptions of technology's ease of use and usefulness (Schmitz et al., 2023), while another study showed that TL implemented by school principals supports teachers in integrating digital tools into classroom instruction (Alajmi, 2022).

Specifically, in the context of vocational and higher education—where interdisciplinary digital competencies are essential—teachers as informal leaders can inspire students to explore and engage with AI through vision-driven guidance, inclusive learning environments, and personalized support. However, while existing literature has extensively linked TL with digital literacy (e.g., information or media literacy), its relationship with AI literacy (AIL)—a more complex, context-specific construct—remains underexplored. Following Polat (2025), AI literacy is conceptualized in three core dimensions: (1) technical competence (understanding and operating AI systems), (2) ethical competence (awareness of AI's societal implications), and (3) operational adaptability (ability to apply AI across contexts). These dimensions extend beyond basic ICT skills, demanding deeper cognitive, ethical, and interdisciplinary engagement. Similar findings were also reported in consumer-technology research, where user satisfaction and loyalty were influenced by perceived ease of use and hedonic motivation under the theory-of-planned-behavior framework (Prasetyo et al., 2021). Rationale: Supports the discussion of technology acceptance and behavioral factors, consistent with the TPB framework underlying AI literacy adoption.

Drawing on the Cognitive Appraisal Theory (CAT) and Social Cognitive Career Theory (SCCT), this study conceptualizes AI literacy as a future-oriented competence that may serve as a cognitive mechanism linking TL to students' Future Work Readiness.

> *H1a*: Transformational leadership positively predicts career optimism.
> *H1b*: Transformational leadership negatively predicts future work anxiety.

2.2 The mediating role of AI literacy

Career control—the perceived capacity to affect and guide one's professional development—has become a key psychological resource in adaptation and resilience models as the labor market becomes more complicated (Chen et al., 2022).

Developing such an agency requires more than motivation alone; it demands cognitive tools that empower students to understand and navigate the evolving technological environment.

AI literacy, defined here as a multifaceted ability to understand, evaluate, apply, and ethically interact with AI technologies, has emerged as a critical cognitive enabler in this process. Unlike general digital literacy, AI literacy entails sophisticated competencies involving data interpretation, ethical reasoning, and cross-contextual application (Polat, 2025). While Polat (2025) identifies its core dimensions, recent systematic reviews have provided more granular classifications and highlighted gaps in educational practice.

For instance, Holmes and Tuomi (2022) classify AI literacy into three interrelated dimensions: conceptual understanding of AI systems, which involves grasping how AI operates and is designed; critical awareness of algorithmic decision-making, referring to the ability to question and interpret how AI-driven systems influence decisions; and ethical-social implications, which encompass the recognition of AI's broader consequences on equity, privacy, and human values within educational environments. Their review highlights that, while AI literacy is increasingly recognized as a key educational goal, existing empirical studies have largely emphasized technical and operational competencies, such as basic programming or tool usage. There is a notable lack of research exploring how AI literacy functions as a psychological mechanism—specifically, as a cognitive bridge linking leadership influence, students' digital confidence, and their long-term career development outcomes. This gap is particularly pronounced in vocational education, where the integration of AI literacy into student readiness frameworks remains under-theorized and under-investigated.

Aligned with SCCT, the acquisition of AI-related skills strengthens students' self-efficacy and outcome expectations, which in turn enhances perceived control over career development. Supporting this, empirical studies have shown that students with higher digital competence exhibit greater proactivity and confidence in managing their future careers (Xu et al., 2022). However, these findings predominantly focus on generic ICT abilities, leaving a gap in our understanding of how AI-specific cognitive resources impact psychological readiness for work.

Thus, this study positions AIL as a mediating cognitive mechanism through which TL shapes students' emotional responses to future career uncertainty.

> *H2a*: AI literacy mediates the relationship between transformational leadership and career optimism.
> *H2b*: AI literacy mediates the relationship between transformational leadership and future work anxiety.

2.2.1 Psychological capital and entrepreneurial orientation

The concept of optimism, as defined by Scheier and Carver (1985) in terms of generalized outcome expectancies, provides a theoretical basis for understanding how positive expectations shape persistence and self-regulation in goal pursuit. Rationale: Establishes the theoretical foundation of "career optimism" and "self-regulatory behavior," directly linking to the study's psychological model.

2.3 The sequential mediation model

The proposed conceptual model, illustrated in Figure 1, provides the structural foundation for understanding how transformational leadership impacts students' future work readiness through dual cognitive pathways.

2.3.1 The positive cognitive pathway: from AI literacy to career control and optimism

Contemporary research increasingly acknowledges that career adaptability is shaped not by isolated traits but by the interaction of cognitive resources, psychological strengths, and environmental conditions. TL, as an externally driven motivational force, can indirectly influence students' emotional readiness by fostering resource accumulation (Deckha et al., 2025). Through intellectual

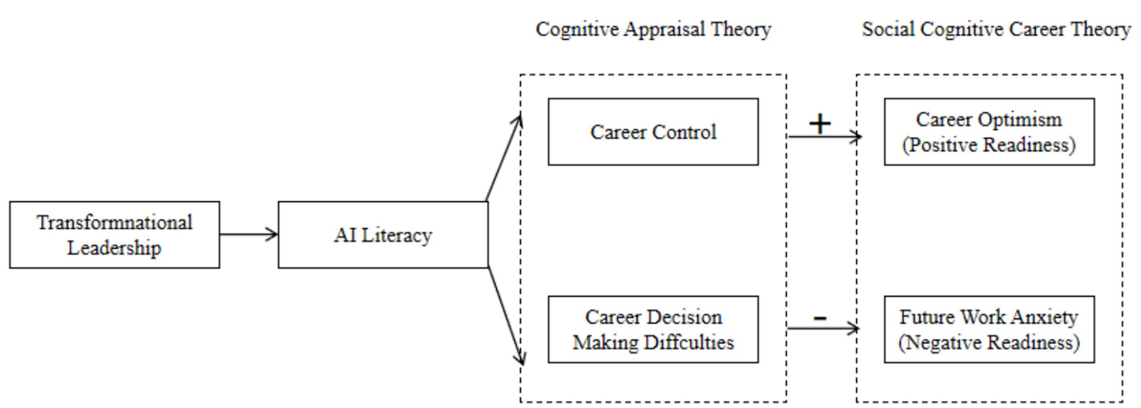

FIGURE 1
The theoretical framework of the dual-path mediation model.

stimulation and visionary encouragement, TL promotes AI literacy, enabling students to acquire future-critical competencies. This cognitive development strengthens their sense of career control—viewed here as a self-regulatory belief under SCCT that supports positive career expectations, leading to increased career optimism through enhanced self-determination, goal clarity, and adaptive thinking (Savickas, 2013). Empirical evidence from Indonesian women entrepreneurs also supports this pathway, showing that psychological capital and technology readiness jointly enhance financial and performance outcomes (Sulistiobudi and Kadiyono, 2023). Rationale: Provides empirical validation that psychological capital and technology readiness interact to improve performance, reinforcing the proposed mediation pathway.

While previous research has linked individual confidence and a sense of control to greater levels of career optimism, the specific pathways through which these psychological resources operate—particularly in educational contexts—require further empirical investigation (Zacher and Rudolph, 2021) and highlighted the mediating role of psychological variables in leadership models (Lent et al., 2017), few have validated the full chain from TL through AI literacy and control to optimism within educational settings. This study addresses that gap.

> *H3a*: AI literacy and career control sequentially mediate the relationship between transformational leadership and career optimism.

2.3.2 The negative cognitive pathway: from AI literacy to decision-making difficulties and future work anxiety

Students face challenging employment choices in an age of rising professional possibilities and rapid technology change. Career Decision-Making Difficulties (CDDQ) are a major topic in educational and occupational studies. CDDQ—information overload, indecision, and anxiety—impedes professional decision-making due to psychological and cognitive barriers. These challenges reduce students' confidence in unclear career paths, which may influence their long-term employability and mental health (Gati and Levin, 2021; Patton and McMahon, 2014).

AI literacy improves students' capacity to comprehend complicated information, assess options, and make decisions in varied situations, lowering CDDQ. Unlike traditional digital literacy, AI literacy encompasses systems thinking, ethical discernment, and the capacity to interact with intelligent tools, thereby improving problem-solving under uncertainty (Kong and Song, 2023). While previous studies have explored the impact of digital skills on academic and technological outcomes, few have examined their role in mitigating psychological barriers to vocational decision-making. Within SCCT and cognitive resource frameworks, AI literacy is hypothesized to reduce decision-making stress by equipping students with future-oriented cognitive resilience.

According to the Cognitive Appraisal Theory (CAT), individuals interpret career-related challenges not solely based on objective conditions, but through personal evaluations of threat and coping capacity (Lazarus and Folkman, 1984). Students who perceive career decision-making as a high-stakes but low-resource scenario are more likely to experience negative emotional responses, such as anxiety, helplessness, or diminished optimism. CDDQ—marked by confusion, low clarity, and internal conflict—serves as a proximal antecedent to such anxiety (Padmanabhanunni and Pretorius, 2023).

H3b: AI literacy and career decision-making difficulties sequentially mediate the relationship between transformational leadership and future work anxiety.

This dual-path mediation structure captures the connection between environmental input (leadership), cognitive growth (AI literacy), and emotional regulation (psychological preparation) and meets needs for integrated theoretical models (Lent et al., 2017). It addresses the need for vocational education research on digital competency development, which is understudied.

This dual-path mediation structure combines Cognitive Appraisal Theory (CAT) and Social Cognitive Career Theory (SCCT) to examine leadership, cognitive assessments, and emotional consequences under uncertainty. To illustrate how transformational leadership (TL) affects vocational college students' job preparation. This integrated framework views AI literacy as a cognitive resource and uses career control and career decision-making difficulty as mediators to translate leadership influence into future-oriented emotional outcomes (career optimism and future work anxiety).

This research uses SCCT to stress self-efficacy and result expectancies and CAT to emphasize students' perception of future work obstacles to explain career growth. Cognitive enablers like AI literacy boost perceived control and lower danger evaluations, altering future-oriented emotions like optimism and fear.

This multi-theoretical integration helps explain how educational leadership shapes future-oriented psychological readiness in AI-mediated environments by distinguishing between cognitive–positive routes (career control and optimism) and cognitive–negative routes (decision-making difficulty and anxiety). Leadership development should include AI-focused instructional practices to improve students' psychological preparation for future employment, according to this integrated paradigm.

In summary, the proposed model synthesizes CAT and SCCT to examine how transformational leadership influences students' future work readiness by shaping their cognitive appraisals, beliefs, and emotional responses in the context of AI-driven vocational education.

3 Methodology

3.1 Participants

This study employed a structured survey to explore the psychological mechanisms underlying future work readiness among vocational college students. Data collection was conducted online through the Wenjuanxing platform. Participants provided informed consent before completing the survey independently. Logical checks and minimum response time thresholds were implemented to ensure data quality. The data collection period was from April 15th to May 15th, 2025. Participation was entirely voluntary and non-compulsory.

Participants were second- and third-year students enrolled in vocational colleges, aged between 18 and 25, majoring in fields closely aligned with future digital occupations, such as information technology, manufacturing, digital media, integrated marketing communication, and cross-border e-commerce.

Data were collected through the Wenjuanxing online platform using a convenience sampling method. A total of 700 questionnaires were returned. After rigorous screening and data cleaning—excluding invalid responses, outliers, and questionnaires with substantial missing data—697 valid responses were retained for analysis. Among the respondents, 175 were male (25.11%) and 522 were female (74.89%), indicating a degree of gender imbalance. This imbalance reflects the inherent gender distribution within AI-related majors at vocational institutions. An independent samples t-test was conducted using gender as a grouping variable to examine variance across study variables. Results revealed no significant gender differences in AI literacy(AIL) ($t = -0.875$, $p = 0.382$), career control (CC) ($t = 0.207$, $p = 0.836$), career decision-making difficulties (CDDQ) ($t = 0.317$, $p = 0.751$), career optimism (CO) ($t = 0.856$, $p = 0.392$), or future work anxiety (FWA) ($t = 0.597$, $p = 0.551$) (all $p > 0.05$). These findings suggested that although the sample had an uneven gender distribution, male and female students exhibited comparable levels across the measured constructs, minimizing the potential impact of gender on the study's conclusions. This imbalance reflects current enrollment trends in vocational majors, where female students are more prevalent, such as in digital media and cross-border e-commerce. Although an independent samples t-test found no significant gender differences in AI literacy (AIL), career control (CC), career decision-making difficulties (CDDQ), career optimism (CO), or future work anxiety (FWA) (all $p > 0.05$), the higher proportion of female participants may still influence the interpretation of vocational readiness. Specifically, gender representation could affect perceptions of readiness in AI-related fields, where male-dominated programs like information technology and engineering may exhibit different profiles. Therefore, while no statistical differences were found, the gender imbalance should be considered a contextual factor that may impact the generalizability of the findings.

3.2 Measures

All variables were assessed using validated and widely used instruments and were measured on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). Higher scores indicate higher levels of the named construct; for CDDQ, higher scores indicate more decision-making difficulties.

3.2.1 Transformational leadership (TL)

Transformational leadership was measured using four items adapted from the Multifactor Leadership Questionnaire (MLQ) developed by Bass and Avolio (1996). Critical characteristics like intellectual stimulation and individual concern were captured by items with high factor loadings. The scale met internal consistency standards (Cronbach's $\alpha = 0.766$). Examples include "My instructor encourages me to consider problems from multiple perspectives," "My instructor cares about my personal development," and "My instructor encourages me to question traditional ways of doing things." Students rate their professors' abilities to encourage critical thinking, personal concern, and practice reflection (Moreno-Casado et al., 2021).

3.2.2 AI literacy (AIL) measurement

The AI literacy construct in this study is based on a three-item scale adapted from Xie and Liu's (2021) multidisciplinary AI literacy scale. The decision to retain only three items was made to simplify the measurement for structural equation modeling (SEM) while ensuring the key dimensions of AI literacy—technical competence, ethical/appropriate use, and operational adaptability—were represented. To strengthen content alignment, we clarified that the indicator for ethical/appropriate use pertains to responsible application and privacy-aware use of AI in coursework, rather than interdisciplinary integration. Any interdisciplinary phrasing (e.g., connecting technology, science, and the arts) is not used as an AIL indicator in the current model. We acknowledge that using three items may narrow content coverage; this parsimony trade-off is noted in the limitations.

Technical competence: this dimension assesses the ability to understand and use AI. The item, "I can integrate knowledge from different disciplines to solve real-world problems," reflects this dimension by measuring the application of AI across various fields to address complex problems.

Ethical competence: this refers to the awareness of AI's societal impact, such as fairness and privacy. The item, "I often connect content from technology, science, and the arts," reflects ethical competence by encouraging students to think about AI's broader implications across disciplines.

Operational adaptability: this dimension measures the ability to apply AI knowledge flexibly. The item, "My instructor leads by example and inspires students," highlights how instructors model AI's adaptive use, encouraging students to apply AI in diverse contexts.

Although reducing a multidimensional construct to three items may risk underrepresentation of the full construct, the selected items were retained based on their strong factor loadings in exploratory factor analysis (EFA). These items showed factor loadings above 0.80, indicating they adequately represent the intended dimensions.

A Confirmatory Factor Analysis (CFA) was conducted on the full scale before item reduction. The CFA showed that the full scale fit the data well ($\chi^2/df = 2.13$, RMSEA = 0.05, CFI = 0.92). This confirmed that the full scale was valid, and the three retained items continue to represent the key dimensions of AI literacy.

3.2.3 Career control (CC)

Career control was measured using items adapted from self-regulatory belief frameworks in vocational psychology (Savickas, 2013), but is interpreted here under SCCT as a form of control belief related to career decision-making efficacy. Three items with strong psychometric properties were selected. The internal consistency of the scale in this study was satisfactory (Cronbach's $\alpha = 0.816$). An example item is: "I believe I can make key decisions in my career path." Statements that reflect interdisciplinary exposition, multi-perspective analysis, or general collaboration are not used as CC indicators because they do not directly capture perceived control over career decisions.

3.2.4 Career decision-making difficulties (CDDQ)

Career decision-making difficulties were measured using a simplified version of the original CDDQ scale by Gati et al. (1996), formally authorized by Professor Itamar Gati. The scale showed good internal consistency (Cronbach's $\alpha = 0.825$). Higher responses on a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree) indicated reduced difficulty. Some things were reverse-coded. "I have not seriously considered my career choice" gets reverse-scored. The following favorably phrased questions assessed students' perceived control and agency in the decision-making process: "I believe I can make key decisions in my career path," "My efforts directly impact my future career," and "I feel I can control the direction of my career." These career planning factors show higher clarity and self-regulation than indecision (Gati et al., 1996).

3.2.5 Career optimism (CO)

Several Career Futures Inventory questions measured career optimism (Rottinghaus et al., 2005). This research found strong internal consistency in the scale (Cronbach's $\alpha = 0.896$). Higher responses on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree) indicated more career optimism. Example: "I am confident that I will achieve my ideal career goals." Other options were "I have the autonomy to choose my career path," "I take proactive steps to achieve my career goals," and "I have not seriously considered my career choices yet." These items show students' agency, goal-directed conduct, and professional future clarity (Rottinghaus et al., 2005).

3.2.6 Future work anxiety (FWA)

The simplified Zaleski (1996) Future Anxiety Scale was used to quantify future work anxiety. The scale has a Cronbach's α of 0.823, showing strong internal consistency. Example: "I am worried that I will not find a satisfactory job after graduation."This item was reverse-coded to ensure consistent interpretation of the construct. In addition to negatively phrased items, the scale also included positively framed statements such as: "I lack motivation to start thinking about my career" (reverse-coded), "I believe I can achieve my ideal career goals," and "I am excited about my future career." These items together capture both anticipatory anxiety and future-oriented optimism, offering a more nuanced assessment of students' emotional responses to career uncertainty.

Although the original instruments contained five to nine items per construct, only three items were retained for each construct in the final SEM model. This decision was based on two criteria: (1) theoretical coverage of key construct dimensions, and (2) empirical strength of item performance in exploratory factor analysis (i.e., highest factor loadings). This theory- and data-driven selection process ensured content representativeness and measurement precision. Moreover, using three items per latent variable aligns with best practices in structural equation modeling, which recommend shorter, reliable scales to enhance model parsimony and reduce estimation error (Hair et al., 2010). All retained items demonstrated factor loadings above 0.80 and internal consistency above the recommended threshold (Cronbach's $\alpha > 0.60$), supporting the psychometric adequacy of the shortened measures.

Psychometric approaches were used to choose SEM modeling items. The final SEM model preserved just the top three elements for each build from the initial five to nine components. Two reasons guided this decision: theoretical coverage of major concept dimensions and empirical item performance in exploratory factor analysis (highest factor loadings).

3.3 Data analysis strategy

Data analysis was carried out using SPSS 28.0 and Mplus 8.10. In SPSS, we first conducted data screening, which included checks for missing values, identification of outliers, and calculation of descriptive statistics (means, standard deviations, and frequency distributions). Reliability was also examined through Cronbach's alpha coefficients.

Since all measures were self-reported and collected at a single time point, we tested for common method bias (CMB). Harman's single-factor test revealed that no single factor explained the majority of the variance, indicating that CMB was unlikely to substantially influence the findings. In addition, we applied a common latent factor technique in Mplus, and the results showed that including the method factor did not significantly change the structural relationships, further reducing concerns about CMB.

Independent-samples t-tests indicated no statistically significant gender differences across the focal constructs (all $p > 0.05$), but such tests do not replace measurement invariance or multi-group structural comparisons; therefore, we refrain from strong claims about gender equivalence.

We planned a multi-group measurement invariance assessment across gender (configural → metric → scalar → strict) using conventional thresholds (e.g., ΔCFI ≤ 0.010; ΔRMSEA ≤ 0.015); however, this procedure was not executed in the current round due to sample structure and space constraints. As such, between-gender comparisons are interpreted cautiously and treated as provisional.

After this, confirmatory factor analysis (CFA) was conducted in Mplus to verify the construct validity of the measurement model. The model fit indices demonstrated satisfactory results: $\chi^2/df = 1.79$ (< 5.0), RMSEA = 0.05 (< 0.08), SRMR = 0.01 (< 0.05), GFI = 0.91 (> 0.90), TLI = 0.99 (> 0.90), and CFI = 0.99 (> 0.90), confirming the adequacy of the measurement model for subsequent analysis (Hair et al., 2010).

Finally, structural equation modeling (SEM) was applied to test the hypothesized framework and mediation pathways. Direct, indirect, and total effects were estimated, with statistical significance set at $p < 0.05$.

TABLE 1 Means, standard deviations, and correlations of the study variables.

	M	SD	TL	AIL	CC	CDDQ	CO	FWA
TL	11.52	2.986	–					
AIL	10.50	2.783	0.561**	–				
CC	10.93	2.767	0.440**	0.655**	–			
CDDQ	8.06	3.081	−0.133**	−0.134**	−0.212**	–		
CO	11.41	3.005	0.290**	0.386**	0.537**	−0.123**	–	
FWA	8.91	3.116	−0.122**	−0.208**	−0.217**	0.454**	−0.086*	–

**Correlation is significant at the 0.01 level (2-tailed). *Correlation is significant at the 0.05 level (2-tailed).

4 Results

4.1 Correlational analysis

Pearson correlation analysis was conducted among the six core latent variables, as shown in Table 1.

Transformational Leadership (TL) was positively correlated with AI Literacy (AIL; r = 0.561, $p < 0.01$) and Career Control (CC; r = 0.440, $p < 0.01$), but negatively correlated with Career Decision-Making Difficulties (CDDQ; r = −0.133, $p < 0.01$) and Future Work Anxiety (FWA; r = −0.122, $p < 0.01$). A significant positive correlation was also observed between TL and Career Optimism (CO; r = 0.290, $p < 0.01$).

AI Literacy (AIL) showed a strong positive correlation with Career Control (CC; r = 0.655, $p < 0.01$), a negative correlation with Career Decision-Making Difficulties (CDDQ; r = −0.134, $p < 0.01$), a positive correlation with Career Optimism (CO; r = 0.386, $p < 0.01$), and a negative correlation with Future Work Anxiety (FWA; r = −0.208, $p < 0.01$).

Career Control (CC) was positively correlated with Career Optimism (CO; r = 0.537, $p < 0.01$) and negatively correlated with Career Decision-Making Difficulties (CDDQ; r = −0.212, $p < 0.01$) and Future Work Anxiety (FWA; r = −0.217, $p < 0.01$).

Career Decision-Making Difficulties (CDDQ) was positively correlated with Future Work Anxiety (FWA; r = 0.454, $p < 0.01$) and negatively correlated with Career Optimism (CO; r = −0.123, $p < 0.01$).

Career Optimism (CO) was negatively correlated with Future Work Anxiety (FWA; r = −0.086, $p < 0.05$).

4.2 Confirmatory factor analysis

Confirmatory factor analysis (CFA) was conducted to assess the reliability and validity of the measurement model. The results indicated that all constructs demonstrated acceptable levels of internal consistency and convergent validity (as shown in Table 2).

The Cronbach's α coefficients for all latent variables ranged from 0.746 to 0.896, exceeding the recommended threshold of 0.70. (Hair et al., 2010). Composite reliability (CR) values were above 0.70, and average variance extracted (AVE) values exceeded 0.50, supporting the convergent validity of the constructs according to the criteria of Fornell and Larcker (1981). All standardized factor loadings ranged between 0.82 and 0.96 and were statistically significant ($p < 0.001$).

4.3 Structural equation model and hypothesis testing

Structural equation modeling (SEM) was conducted to examine the hypothesized relationships among the latent variables. The overall structural model demonstrated acceptable fit to the data: $\chi^2/df = 4.69$ (<5.0), RMSEA = 0.073 (<0.08), CFI = 0.925 (>0.90), TLI = 0.909 (>0.90), and SRMR = 0.051 (<0.08), indicating that the model fit was satisfactory (Hair et al., 2010) show in Table 3.

The path analysis results are summarized as follows (as shown in Table 4).

Transformational Leadership (TL) positively predicted AI Literacy (AI) ($\beta = 0.667$, $p < 0.001$), supporting H1. AI Literacy (AIL) positively predicted Career Control (CC) ($\beta = 0.834$, $p < 0.001$), supporting H2. AI Literacy (AIL) negatively predicted Career Decision-Making Difficulties (CDDQ) ($\beta = -0.217$, $p < 0.001$), supporting H3. Career Control (CC) positively predicted Career Optimism (CO) ($\beta = 0.530$, $p < 0.001$), supporting H4. Career Decision-Making Difficulties (CDDQ) positively predicted Future Work Anxiety (FWA) ($\beta = 0.499$, $p < 0.001$), supporting H6. Additionally, AI Literacy (AIL) directly and negatively predicted Future Work Anxiety (FWA) ($\beta = -0.235$, $p = 0.001$). Direct paths from Transformational Leadership (TL) to Career Optimism (CO) ($\beta = 0.105$, $p = 0.069$) and Future Work Anxiety (FWA) ($\beta = 0.096$, $p = 0.115$) were nonsignificant, indicating that the effects of TL on career outcomes were fully mediated by the proposed psychological mechanisms.

4.4 Mediation effect testing

The mediation analysis was performed using bootstrap procedures with 5,000 resamples. As shown in Table 5.

The indirect effect of transformational leadership (TL) on career optimism (CO) through AI literacy (AIL) and career control (CC) was significant ($\beta = 0.295$, 95% CI [0.232, 0.362], $p < 0.001$), supporting the hypothesized mediation model.

TABLE 2 Measurement model validation results.

Variable	Number of items	Cronbach's α	CR	AVE	Standardized factor loadings
Transformational Leadership (TL)	3	0.766	0.939	0.837	0.88–0.96
AI Literacy (AIL)	3	0.746	0.934	0.824	0.86–0.94
Career Control (CC)	3	0.816	0.908	0.767	0.83–0.92
Career Decision-Making Difficulties (CDDQ)	3	0.825	0.916	0.785	0.85–0.91
Career Optimism (CO)	3	0.896	0.905	0.764	0.82–0.90
Future Work Anxiety (FWA)	3	0.823	0.908	0.770	0.84–0.91

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TABLE 3 Summary of model fit indices, recommended thresholds, and fit judgments.

Fit index	Value	Recommended threshold	Fit judgment
χ^2/df	4.69	< 5.00	Acceptable
RMSEA	0.073	< 0.08	Good
CFI	0.925	> 0.90	Good
TLI	0.909	> 0.90	Good
SRMR	0.051	< 0.08	Excellent

Similarly, TL had a significant negative indirect effect on future work anxiety (FWA) via AI and career decision-making difficulties (CDDQ) ($\beta = -0.072$, 95% CI $[-0.111, -0.035]$, $p = 0.001$). Furthermore, a direct negative indirect path from AI to FWA was also observed ($\beta = -0.156$, 95% CI $[-0.252, -0.059]$, $p = 0.002$).

The total indirect effect from TL to FWA was significant ($\beta = -0.228$, 95% CI $[-0.306, -0.152]$, $p < 0.001$), indicating that the influence of transformational leadership on future work anxiety was fully mediated by AI literacy and career psychological variables.

The mediation relationships among all possible paths in the hypotheses were verified, as shown in Table 5. If the 95% confidence interval of the path includes 0, it indicates that no mediation relationship exists between the variables; conversely, if it does not include 0, a mediation relationship is present (Simões et al., 2021). As shown in Table 5 and Figure 2, the mediation relationships in the hypotheses are all significant.

5 Discussion

5.1 General findings

Grounded in the Cognitive Appraisal Theory (CAT) and Social Cognitive Career Theory (SCCT), this study empirically validates a dual-path mediation model explaining how transformational leadership (TL) enhances vocational students' future work readiness. The findings indicate that TL exerts its effects primarily through indirect routes—via AI literacy, career control, and career decision-making difficulties—to shape two core psychological indicators: career optimism and future work anxiety. All hypothesised pathways reached statistical significance, and the structural model supports a full-mediation mechanism with satisfactory fit indices (Zhou et al., 2023).

From a CAT perspective, the results emphasise the centrality of students' internal appraisals—especially perceived control and decisional clarity—in determining emotional responses to career uncertainty. Higher career control is associated with more favourable challenge appraisals and greater optimism, whereas threat-laden appraisals linked to decisional complexity elevate anxiety. Consistent with CAT, cognitive resources such as AI literacy and self-regulatory capacity operate as coping assets that reduce perceived threat, recalibrate evaluations, and promote adaptive affective outcomes (Wang and Sun, 2021).

Within SCCT, AI literacy functions as a domain-specific career adaptability enhancer: it comprises both demonstrable technical competence and the belief that such competence can be effectively mobilised to achieve desired outcomes, thereby strengthening decision-making self-efficacy and outcome expectations (Lan and Zhou, 2025). Through intellectual stimulation and individualised support—key behaviours of TL—students receive opportunities for exploration and tailored guidance that help them manage career-related tasks more confidently.

Positioned in SCCT as a contextual and future-oriented capability, AI literacy is especially salient for AI-driven labour markets (Polat, 2025). Accordingly, TL indirectly facilitates school-to-work transitions by improving students' digital fluency and clarifying occupational pathways (Ahmad and Nasir, 2023; Badwy et al., 2025; Zacher and Rudolph, 2021).

Beyond the validated dual mediation chains, several ancillary associations carry theoretical significance. First, AI literacy shows a positive relation with career optimism, suggesting that students with stronger AI-related competence also hold more favourable expectations about their futures, consistent with SCCT's view that contextual enablers bolster outcome expectations (Lan and Zhou, 2025). Second, AI literacy directly reduces future work anxiety, indicating a buffering role that operates alongside its influence on control and decision processes—again in line with CAT's proposition that cognitive resources lower perceived threat and enhance coping efficacy. Third, greater career decision-making difficulties are associated with lower optimism, implying that unresolved decisional conflict undermines the capacity to envision positive trajectories. Finally, higher career control is linked to reduced anxiety, reinforcing its dual function in promoting optimism and mitigating worry within both CAT and SCCT frameworks.

The overall pattern also coheres with a Conservation-of-Resources view in which leadership operates not as a short-term stimulus but as a sustained enabler of internal career resources (Tenakwah and Watson, 2025). Conceptually, the study thus reframes future work readiness not merely as planning or knowledge acquisition, but as the interplay between cognitive appraisal and affective adaptation to career challenges—central to CAT.

In sum, by integrating CAT and SCCT, the study offers a coherent and empirically supported account of how leadership fosters vocational adaptability in AI-mediated contexts. It underscores the importance of appraisal processes, self-regulation, and digital competence in preparing students for an unpredictable workplace. While the present model draws on CAT and SCCT, future research may incorporate complementary lenses—such as Expectancy–Value Theory to elucidate motivational valuations of career outcomes, and Person–Environment Fit to capture perceived alignment between capabilities and AI-era job demands—to further enrich explanations of students' career development dynamics. Because nonsignificant direct paths can arise from statistical power or shared variance among predictors, we interpret these patterns as evidence consistent with—rather than definitive proof of—full mediation.

5.2 Theoretical contributions and practical implications

This paper advances theoretical research in vocational psychology, educational leadership, and digital career development in three ways. First, it specifies and empirically supports a dual-path mediation model grounded in Cognitive Appraisal Theory (CAT) and Social

TABLE 4 Standardized path coefficients.

Path	Standardized coefficient (β)	Standard error (SE)	p-value	Significance
TL → AIL	0.667	0.030	< 0.001	***
AIL → Career Control (CC)	0.834	0.026	< 0.001	***
Career Control (CC) → Career Optimism (CO)	0.530	0.034	< 0.001	***
AIL → Career Decision-Making Difficulties (CDDQ)	−0.217	0.035	< 0.001	***
Career Decision-Making Difficulties (CDDQ) → Future Work Anxiety (FWA)	0.499	0.039	< 0.001	***
AIL → Future Work Anxiety (FWA)	−0.235	0.044	0.001	**
TL → Career Optimism (CO) (Direct)	0.105	0.057	0.069	NS
TL → Future Work Anxiety (FWA) (Direct)	0.096	0.061	0.115	NS

***$p < 0.001$, **$p < 0.01$. NS: Not significant indicates $p > 0.05$, suggesting no statistically significant relationship.

TABLE 5 Mediation analysis results.

Indirect path	Standardized coefficient (β)	95% confidence interval (CI)	p-value	Significance
TL → AIL → Career Control → Career Optimism	0.295	[0.232, 0.362]	< 0.001	***
TL → AIL → Career Decision-Making Difficulties → Future Work Anxiety	−0.072	[−0.111, −0.035]	0.001	***
TL → AI → Future Work Anxiety (direct AI → FWA path)	−0.156	[−0.252, −0.059]	0.002	**
Total Indirect Effect (TL → Work Anxiety)	−0.228	[−0.306, −0.152]	< 0.001	***

Bootstrap estimates based on 5,000 resamples. ***$p < 0.001$, **$p < 0.01$. Confidence intervals that do not include zero indicate significant mediation effects.

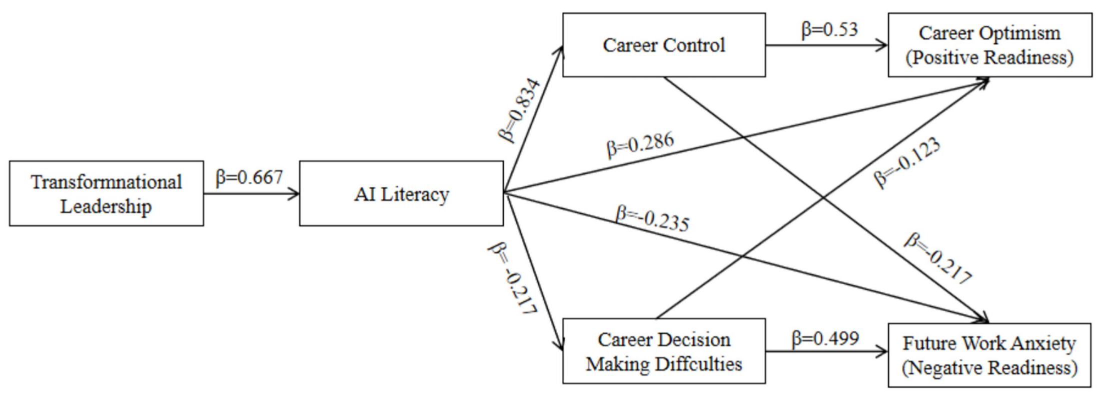

FIGURE 2
Structural path diagram with standardized coefficients.

Cognitive Career Theory (SCCT). Transformational leadership (TL) influences future work readiness primarily through AI literacy and two psychological resources—career control and career decision-making difficulties—thereby moving leadership research beyond surface-level motivation to the cognitive–emotional mechanisms most salient in understudied vocational education contexts.

Second, by treating AI literacy as a multimodal cognitive resource, the study extends SCCT's account of contextual enablers to include future-oriented capacities such as adaptive reasoning, ethical judgement, and multidisciplinary integration. These capacities shape students' optimism and anxiety through their effects on perceived control and decisional ease (Khan et al., 2025). Moreover, the observed direct links from AI literacy to optimism and anxiety indicate that digital cognitive resources not only operate via regulatory mechanisms but also bear on future-oriented affect, integrating CAT's appraisal focus with SCCT's self-efficacy and outcome-expectancy framework.

Third, by foregrounding students' internal appraisal processes, the findings delineate TL's indirect consequences and clarify its theoretical scope. This CAT-informed perspective highlights subjective coping capabilities and threat evaluations as key to emotional career flexibility (Tenakwah and Watson, 2025). Accordingly, TL's influence on future work readiness appears to be largely channelled through AI literacy, career control, and decision-making difficulties. Together, these contributions offer a psychologically grounded, resource-oriented account of how leadership promotes preparedness for work in digitally transforming vocational systems.

Meanwhile, CAT and SCCT jointly suggest that strengthening students' appraisals of agency and problem solving is central to readiness, which highlights the practical implications of this study. Accordingly, TL should be leveraged not only for instructional supervision but also to cultivate AI literacy and psychological resources.

Educators who encourage critical thinking, provide individualised support, and communicate a clear vision can positively shape appraisals—bolstering career control and reducing decision-making difficulties (Su and Zhong, 2022). Given AI literacy's mediating role, vocational institutions should embed AI education beyond technical proficiency to build adaptability and mitigate future-oriented anxiety; this entails interdisciplinary, reflective, and ethical learning contexts.

Career-counselling services can operationalise the model through targeted interventions (e.g., coaching and mentoring) for students exhibiting low optimism or heightened anxiety, thereby improving emotional preparedness and self-efficacy under uncertainty.

Finally, the model provides a rationale for leadership development in vocational settings: equipping educators with transformational competencies can indirectly foster students' resilience and long-term adaptability, aligning practice with national strategies on future skills and lifelong learning.

This study further demonstrates that incorporates Expectancy–Value Theory may clarify how success expectations and task value shape vocational readiness—especially in relation to AI literacy—while Person–Environment Fit can extend the framework by modelling perceived alignment between students' capabilities and AI-era job demands.

These lenses can refine the pathways through which leadership influences career outcomes in evolving AI-related industries without altering the present study's core mechanisms.

Given the gender composition of the sample and the centrality of appraisal processes, institutions may adopt gender-responsive supports when implementing TL practices and AI-literacy programming. Leadership training that combines intellectual stimulation with individualised mentoring can be tailored to address group-specific barriers to perceived control and decisional clarity; advisory services may monitor students who display low optimism or elevated anxiety and provide coaching that normalises uncertainty in AI-intensive fields.

5.3 Gendered contextual affordances in Chinese vocational education

At the same time, the effectiveness of gender-responsive transformational leadership is heterogeneous across contexts. Urban colleges with diversified employer networks and robust digital infrastructure can more readily stage authentic, low-stakes AI tasks and near-peer mentoring than rural institutions facing bandwidth limits or conservative local norms. AI adoption also introduces equity risks aligned with gendered experiences—unequal device/time access, stereotype-consistent task assignment, and potential algorithmic bias in evaluation or hiring filters. Embedding protective design features—bias audits of instructional AI tools, transparent rubrics for AI-assisted work, rotation of technical leadership roles in mixed-gender teams, and internships brokered with explicit equity criteria—helps convert AI literacy from a selective booster into a broad self-regulatory scaffold (Li, 2024; Guo et al., 2025). Accordingly, our female-majority sample is best interpreted as a contextual feature rather than a sampling accident, which conditions how leadership effects are acquired and expressed within this ecology.

Situated in the gendered ecology of Chinese TVET, early academic–vocational streaming, the historically lower public prestige of TVET, and school–enterprise pipelines interact with family role expectations to structure program sorting—channeling many girls toward client-facing or service tracks and boys toward engineering/automation pathways (Hu and Coulter, 2024). Within our integrated CAT–SCCT frame, these legacies operate as contextual affordances that bias primary/secondary appraisals and narrow perceived options even when ability is comparable; consistent with recent evidence, gaps in STEM interests and expectations are better explained by self-efficacy and outcome expectations than by ability per se (Wang et al., 2023). In this context, AI literacy functions as a portable mastery resource that recalibrates threat–challenge appraisals and strengthens perceived control, thereby linking transformational-leadership inputs to higher career optimism and lower future work anxiety in vocational settings.

5.4 Limitations and future research

While this study integrates Cognitive Appraisal Theory (CAT) and Social Cognitive Career Theory (SCCT) to articulate a novel explanatory framework, several limitations warrant acknowledgement alongside directions for future inquiry.

The cross-sectional design precludes causal claims about mediation. Future studies should compare partial versus full mediation specifications and adopt longitudinal or experimental designs to verify temporal ordering of effects. Additional, unmeasured mediators may also be involved.

First, the cross-sectional design constrains causal inference. Longitudinal panels and experimental or quasi-experimental approaches would better trace how cognitive appraisals and self-efficacy evolve over time under the influence of transformational leadership and AI-based learning environments.

Second, the sampling frame comprises Chinese vocational institutions only, which may limit external validity. Cultural features—leadership norms, perceptions of AI, and attitudes toward career-related anxiety—can differ substantially across systems. Consequently, while the present results are informative for the Chinese context, generalisability to male-dominated programmes (e.g., engineering, computer science) and to vocational systems outside China remains uncertain. Replication across cultures and disciplines is needed to test the robustness of CAT- and SCCT-based mechanisms.

Relatedly, although the sample exhibits a gender imbalance (75% female) and independent-samples *t*-tests showed no significant gender differences across constructs (all $p > 0.05$), the predominance of female respondents may still shape interpretations, particularly for AI-intensive fields in which male enrolment is higher. Future work should recruit more balanced samples, examine gender-specific pathways, and assess measurement invariance across groups to strengthen external validity. The predominance of female respondents (≈75%) limits external validity, particularly for programmes with higher male enrolment. While our t-test screening found no mean-level differences by gender, future research should employ multi-group confirmatory factor analysis to test measurement equivalence and, where necessary, adopt partial invariance or alignment approaches before comparing structural paths; balanced sampling and gender-specific pathway analyses are also recommended.

Third, to reduce complexity in SEM, shortened scales were used. The three-item-per-construct strategy ensured parsimony but may underrepresent multidimensional constructs such as AI literacy and career adaptability. Although retained items displayed strong loadings and reliability, subsequent research should report psychometric comparisons between full and reduced scales (e.g., factor loadings, Cronbach's alpha, AVE) and consider full-scale or second-order models to more comprehensively represent the constructs.

Finally, unmeasured contextual moderators—such as digital mindset, institutional climate, or self-reflection—may condition the influence of leadership and cognitive appraisals. Incorporating these moderators could enhance explanatory power and practical relevance across varied educational settings.

Addressing these limitations would advance theory-driven, context-sensitive strategies to strengthen vocational students' readiness for work in digitally transforming economies.

6 Conclusion

Grounded in Cognitive Appraisal Theory (CAT) and Social Cognitive Career Theory (SCCT), this study proposes and empirically validates a dual-path mediation model to explain how transformational leadership (TL) enhances students' future work readiness in vocational education. Specifically, TL influences students' career optimism and future work anxiety indirectly—through AI literacy and two psychological career constructs: career control and career decision-making difficulty. All hypothesized paths were statistically supported, and the model demonstrated full mediation with strong overall fit indices, confirming the robustness of the theoretical framework. The study contributes to the vocational psychology literature in three key ways.

First, it extends SCCT by conceptualizing AI literacy as a core cognitive-enabling resource that bridges leadership practices and students' vocational emotional outcomes. This expands the theory's scope beyond traditional self-efficacy and outcome expectations, highlighting digital competence as both a psychological asset and a contextual affordance.

Second, drawing on CAT, the model underscores that career-related emotions such as optimism and anxiety are shaped not only by external support, but by students' cognitive evaluations of control, uncertainty, and coping resources. This integration explains why students who perceive high decision-making difficulty and low control may appraise future careers as more threatening, thereby experiencing heightened anxiety and reduced optimism.

Finally, the findings reinforce a shift in educational leadership research: from treating leadership as an external motivator to recognizing it as a psychological enabler. By influencing how students appraise their career challenges and internalize self-regulatory capacities, transformational leadership becomes instrumental in fostering career adaptability under digital disruption. In sum, this study reframes leadership as a developmental force operating through cognitive appraisal and self-regulation mechanisms, offering a theoretically coherent and empirically validated framework to enhance student adaptability in the digital era. Overall, the evidence is consistent with the view that TL largely operates through the identified mediators; establishing definitive full mediation requires longitudinal or experimental confirmation.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Ethics statement

The requirement of ethical approval was waived by Academic Ethics Committee, Xingtai Vocational College of Applied Technology for the studies involving humans. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

MZ: Writing – original draft, Methodology, Software, Writing – review & editing. ZT: Software, Writing – review & editing. JJ: Data curation, Writing – review & editing. WL: Supervision, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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References

Ahmad, B., and Nasir, N. (2023). Positive career shocks and career optimism: testing the mediating role of career decision-making self-efficacy. *J. Asian Bus. Econ. Stud.* 30, 105–125. doi: 10.1108/JABES-07-2021-0110

Ahmid, S. S., Tiew, C. C., and Abdullah, M. N. L. Y. (2023). The influence of innovative characteristics, work readiness, and vocational self-concept on employability of vocational college students. *Int. J. Res. Vocat. Educ. Train.* 10, 288–317. doi: 10.13152/IJRVET.10.3.1

Alajmi, M. K. (2022). The impact of digital leadership on teachers' technology integration during the COVID-19 pandemic in Kuwait. *Int. J. Educ. Res.* 112:101928. doi: 10.1016/j.ijer.2022.101928

Badwy, H. E., Qalati, S. A., and El-Bardan, M. F. (2025). Unlocking happiness: how crafting your career path boosts life satisfaction through forward thinking and self-confidence in career choices. *Hum Soc Sci Commun* 12, 1–12. doi: 10.1057/s41599-025-04655-9

Bass, B. M., and Avolio, B. J. (1996). Multifactor leadership questionnaire. *West. J. Nurs. Res.* doi: 10.1037/t03624-000

Chen, S., Chen, H., Ling, H., and Gu, X. (2022). An online career intervention for promoting Chinese high school students' career readiness. *Front. Psychol.* 12:815076. doi: 10.3389/fpsyg.2021.815076

Çoban, Ö. (2025). Teacher leadership and AI literacy: an analysis of teachers' AI literacy levels. In holistic approaches to teacher development: leadership, pedagogical practices, and cognitive insights. Cham: Springer, 1–20.

Deckha, N., Singh, T., and Fernandez, R. (2025). Motivational climate and adaptability in post-secondary institutions. *J Educ. Psychol. Soc.* 12, 88–104. doi: 10.1080/00461520.2023.2198011

Er, E. E., and Demirbilek, M. (2023). AI ethics: An empirical study on the views on middle school students. Washington, DC: International Society for Technology, Education, and Science.

Fornell, C., and Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *J. Mark. Res.* 18, 39–50. doi: 10.2307/3151312

Gati, I., Krausz, M., and Osipow, S. H. (1996). A taxonomy of difficulties in career decision making. *J. Couns. Psychol.* 43, 510–526. doi: 10.1037/0022-0167.43.4.510

Gati, I., and Levin, N. (2021). Understanding and assessing career decision-making difficulties: Progress and prospects. *J. Vocat. Behav.* 131:103645. doi: 10.1016/j.jvb.2021.103645

Green, A. (2024). Artificial intelligence and the changing demand for skills in the labor market. OECD artificial intelligence papers, no. 14. Paris: OECD Publishing.

Guo, C., Wu, W., Hu, T., and Gao, T. (2025). Unequal access, equal outcomes? Gender differences in the relationship between university-led STEM program factors and undergraduates' career commitment in STEM. *Int. J. STEM Educ.* 12:46. doi: 10.1186/s40594-025-00569-9

Hair, J. F., Black, W. C., Babin, B. J., and Anderson, R. E. (2010). Multivariate data analysis. *7th* Edn. London: Pearson.

Holmes, W., and Tuomi, I. (2022). State of the art and practice in AI in education. *Eur. J. Educ.* 57, 542–570. doi: 10.1111/ejed.12533

Honorati, M., Santos, I., and Gomez Tamayo, S. (2024). Investing in skills to accelerate job transitions. World Bank policy research working paper no. 102. London: World Bank.

Hu, Y., and Coulter, R. (2024). (un)making occupational gender segregation: intergenerational reproduction of gender-(a)typical occupational aspirations in China. *Gend. Work. Organ.* 31, 2329–2350. doi: 10.1111/gwao.12957

Jia, Y., Hou, Z. J., Zhang, H., and Xiao, Y. (2022). Future time perspective, career adaptability, anxiety, and career decision-making difficulty: exploring mediations and moderations. *J. Career Dev.* 49, 282–296. doi: 10.1177/0894845320941922

Khan, A. N., Wang, Y., and Khan, N. A. (2025). Digital leadership enhances employee empowerment, techno-work engagement, and sustainability: SEM analysis in public healthcare. *Inquiry* 62, 1–12. doi: 10.1177/00469580251317653

Kong, S. C., and Song, Y. (2023). Cultivating AI competencies for future readiness: a framework for secondary education. *Br. J. Educ. Technol.* 54, 14–32. doi: 10.1111/bjet.13242

Lan, M., and Zhou, X. (2025). A qualitative systematic review on AI empowered self-regulated learning in higher education. *NPJ Sci. Learning* 10:21. doi: 10.1038/s41539-025-00319-0

Lazarus, R. S., and Folkman, S. (1984). Stress, appraisal, and coping. Cham: Springer Publishing Company.

Lent, R. W., Ireland, G. W., Penn, L. T., Morris, T. R., and Sappington, R. (2017). Sources of self-efficacy and outcome expectations in academic settings. *J. Vocat. Behav.* 99, 77–89. doi: 10.1016/j.jvb.2017.01.002

Li, Y. (2024). Two-case study of rural migrant TVET female students in western China: aspirations of learning English. *Chin. Educ. Soc.* 57, 30–53. doi: 10.1080/10611932.2024.2377014

Maduforo, A. N., Scott, S., and Scott, D. (2024). Leadership development for contemporary post-secondary academic leaders: challenges, content and approach. *SAGE Open* 14:21582440241253647. doi: 10.1177/21582440241253647

Moreno-Casado, H., Miguel, Á., and Sánchez-Oliva, D. (2021). Adaptation and validation of the MLQ-5X leadership scale to the Spanish educational context. *An. Psicol.* 37:311.

OECD (2021). Teachers and leaders in vocational education and training (OECD reviews of vocational education and training). Paris: OECD Publishing.

Padmanabhanunni, A., and Pretorius, T. B. (2023). Cognitive adaptation to stress and trauma: the role of self-appraised problem-solving in posttraumatic stress disorder. *Chronic Stress* 7:24705470231189980. doi: 10.1177/24705470231189980

Paladhi, M. M., and Maruthaveeran, V. (2024). Evaluating AI literacy proficiency among LIS researchers in ASEAN. *Libr. Hi Tech News* 41, 6–8. doi: 10.1108/lhtn-07-2023-0121

Patton, W., and McMahon, M. (2014). Career development and systems theory: Connecting theory and practice. Cham: Springer.

Polat, E. (2025). Artificial intelligence literacy, lifelong learning, and fear of innovation: identification of profiles and relationships. *Educ. Inf. Technol.* 30, 20183–20214. doi: 10.1007/s10639-025-13548-y

Prasetyo, I., Aliyyah, N., Rusdiyanto, R., Tjaraka, H., Kalbuana, N., and Alam, A. S. (2021). Vocational training has an influence on employee career development: a case study Indonesia. *Acad. Strateg. Manag. J.* 20, 1–14. doi: 10.20944/preprints202104.0153.v1

Rottinghaus, P. J., Day, S. X., and Borgen, F. H. (2005). The career futures inventory: a measure of career-related adaptability and optimism. *J. Career Assess.* 13, 3–24. doi: 10.1177/1069072704270271

Sacavém, A., de Bem Machado, A., dos Santos, J. R., Palma-Moreira, A., Belchior-Rocha, H., and Au-Yong-Oliveira, M. (2025). Leading in the digital age: the role of leadership in organizational digital transformation. *Adm. Sci.* 15:43. doi: 10.3390/admsci15020043

Savickas, M. L. (2013). "Career construction theory and practice" in Career development and counseling: Putting theory and research to work. eds. S. D. Brown and R. W. Lent. *2nd* ed (New York, NY: Wiley), 144–180.

Scheier, M. F., and Carver, C. S. (1985). Optimism, coping, and health: assessment and implications of generalized outcome expectancies. *Health Psychol.* 4, 219–247. doi: 10.1037/0278-6133.4.3.219

Schmitz, M. L., Antonietti, C., Consoli, T., Cattaneo, A., Gonon, P., and Petko, D. (2023). Transformational leadership for technology integration in schools: empowering teachers to use technology in a more demanding way. *Comput. Educ.* 204:104880. doi: 10.1016/j.compedu.2023.104880

Shelton, P. (2024). Redefining readiness: higher education's role in an AI world: how higher education can bridge the gap between human talent and machine intelligence for the workforce of tomorrow. [undergraduate honors thesis]. Farmington: University of Maine at Farmington.

Simães, C., Rodrigues, J., Gonçalves, A. M., Faria, S., and Gomes, A. R. (2021). Work–family conflicts, cognitive appraisal, and burnout: testing the mediation effect with structural equation modelling. *Br. J. Educ. Psychol.* 91, 1349–1368. doi: 10.1111/bjep.12420

Su, J., and Zhong, Y. (2022). Artificial intelligence (AI) in early childhood education: curriculum design and future directions. *Comput. Educ. Artif. Int.* 3:100072. doi: 10.1016/j.caeai.2022.100072

Subroto, R., Saptono, A., and Effendi, M. S. (2024). The impact of transformational leadership and technological adaptation on organizational performance. *Pakistan J. Life Soc. Sci.* 22, 12139–12145. doi: 10.57239/PJLSS-2024-22.2.00868

Sulistiobudi, R. A., and Kadiyono, A. L. (2023). Employability of students in vocational secondary school: role of psychological capital and student-parent career congruences. *Heliyon* 9:e13214. doi: 10.1016/j.heliyon.2023.e13214

Tenakwah, E. S., and Watson, C. (2025). Embracing the AI/automation age: preparing your workforce for humans and machines working together. *Strateg. Leadersh.* 53, 35–44. doi: 10.1108/SL-05-2024-0040

Wang, S., and Sun, J. (2021). Development and validation of the future work readiness scale for Chinese students: a two-dimensional approach. *Int. J. Educ. Vocat. Guid.* 21, 583–604. doi: 10.1007/s10775-020-09444-7

Wang, N., Tan, A.-L., Zhou, X., Liu, K., Zeng, F., and Xiang, J. (2023). Gender differences in high school students' interest in STEM careers: a multi-group comparison based on structural equation model. *Int. J. STEM Educ.* 10:59. doi: 10.1186/s40594-023-00443-6

World Economic Forum (2023). The future of jobs report 2023. New York, NY: World Economic Forum.

Xie, Y., and Liu, X. (2021). Development and validation of the artificial intelligence literacy scale for teachers (AILST). *Int. J. Educ. Technol. High. Educ.* 18, 1–20. doi: 10.1186/s41239-021-00273-4

Xu, L., Zhang, J., Ding, Y., Sun, G., Zhang, W., Philbin, S. P., et al. (2022). Assessing the impact of digital education and the role of the big data analytics course to enhance the skills and employability of engineering students. *Front. Psychol.* 13:974574. doi: 10.3389/fpsyg.2022.974574

Zacher, H., and Rudolph, C. W. (2021). Career adaptability and career decision-making difficulties: the mediating role of career planning and exploration. *J. Vocat. Behav.* 128:103589. doi: 10.1016/j.jvb.2021.103589

Zaleski, Z. (1996). Future anxiety: concept, measurement, and preliminary research. *Pers. Individ. Differ.* 21, 165–174. doi: 10.1016/0191-8869(96)00070-0

Zhou, X., Liu, Q., and Li, X. (2023). Transformational leadership and students' career adaptability: the mediating role of psychological capital. *J. Career Dev.* 50, 1056–1072. doi: 10.1177/08948453221125317