Enhancing Vocational Graduate Employability through Mobile Application on Advanced Quantitative Modeling of Skills and Partnerships

Yang WANG
Vocational Education Division, Faculty of Technical Education, Rajamangala University of Technology Thanyaburi, Pathum Thani 12110, Thailand.
wang_ya@mail.rmutt.ac.th, ORCID:0009-0000-3789-7964

Thosporn SANGSAWANG
Educational Technology and Communications Division, Faculty of Technical Education, Rajamangala University of Technology Thanyaburi, Pathum Thani 12110, Thailand.
**corresponding author: sthosporn@rmutt.ac.th, ORCID:0000-0002-7926-6949*

Abstract
This study investigates the multidimensional factors influencing employability among vocational students in China by applying an advanced quantitative framework. Data were collected from 17 experts, 100 faculty members, and 30 students, and analyzed using a sequential process of Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and Structural Equation Modeling (SEM). EFA extracted six constructs-Professional Skills, Soft Skills, Career Guidance, Industry-Academia Collaboration, Technological Literacy, and Employability Outcomes-explaining 72.6% of total variance. CFA confirmed measurement validity and reliability (Cronbach's $\alpha > 0.80$; CR > 0.84; AVE > 0.50; HTMT < 0.85). SEM results demonstrated that all hypothesized relationships were supported, with Soft Skills ($\beta = 0.35$) identified as the strongest predictor of employability, followed by Professional Skills ($\beta = 0.29$), Technological Literacy ($\beta = 0.24$), Industry-Academia Collaboration ($\beta = 0.21$), and Career Guidance ($\beta = 0.18$). Mediation analysis revealed that Career Guidance indirectly influenced employability through Soft Skills ($\beta = 0.12$, $p < 0.01$), while moderation analysis confirmed that Industry-Academia Collaboration enhanced the effect of Professional Skills on employability ($\beta = 0.09$, $p < 0.05$). The structural model accounted for 68% of variance ($R^2 = 0.68$) in employability outcomes, demonstrating strong explanatory power. The novelty of this research lies in integrating mediation and moderation mechanisms within a validated employability model, moving beyond traditional exploratory methods. Conceptually, the findings highlighted the centrality of Soft Skills in determining employability, challenging the dominance of technical training in vocational education. Practically, the study provides evidence-based recommendations for balancing technical and soft skill training, strengthening career guidance services, and deepening industry-academia partnerships to enhance graduate competitiveness in dynamic labor markets through a Mobile Application on Advanced Quantitative Modeling of Skills and Partnerships.
Keyword: Industry-Academia Collaboration; Technological Literacy; Exploratory Factor Analysis; Mobile Application

Introduction
Vocational education has emerged as a crucial driver for bridging the gap between academic learning and labor market requirements, especially in countries experiencing rapid economic growth such as China [1]. With the transition from elite to mass higher education in the 1990s, the number of graduates has surged dramatically, reaching over 11 million in 2023, thereby intensifying job market competition [2]. This massification of higher education has created an unprecedented challenge: many graduates face unemployment or underemployment due to the misalignment between acquired academic qualifications and the dynamic needs of the labor market [3].

Scholars and policymakers agree that employability is a multidimensional construct that extends beyond technical competence [4]. It encompasses soft skills, adaptability, problem-solving, resilience, career planning, industry exposure, and technological literacy [5]. Employers increasingly emphasize interpersonal communication, teamwork, creativity, and digital readiness as essential attributes [6]. However, research indicates that many higher vocational colleges in China continue to focus primarily on theoretical instruction and do not adequately integrate practical training, career guidance, or industry collaboration into their curricula [7]. This mismatch not only undermines graduates' career prospects but also restricts the country's ability to cultivate a globally competitive workforce.

To address this issue, the Chinese government has enacted multiple policies such as the 2015 *Opinions on Strengthening the Employment of University Graduates* and the 2020 *Notice on Doing a Good Job in Graduate*

Employment and Entrepreneurship [8]. These initiatives emphasize job training, entrepreneurial support, and career guidance. While such policies have advanced employability services, existing academic research has largely relied on exploratory methods such as descriptive analysis and exploratory factor analysis (EFA) to identify determinants of employability [9]. These methods are useful for identifying factors but are limited in their ability to test causal relationships and validate multidimensional constructs across diverse student populations.

This study introduces a novel framework by integrating advanced quantitative methodologies including exploratory factor analysis (EFA), confirmatory factor analysis (CFA), and structural equation modeling (SEM). Unlike prior studies that stop at identifying factors, this research validates the employability model through CFA and examines causal pathways among variables using SEM [10]. For instance, the study tests how *career guidance* indirectly shapes employability through the development of *soft skills*, while *industry-academia collaboration* moderates the relationship between *professional skills* and employment outcomes. This multi-layered approach not only identifies which factors matter most but also explains how and why they influence employability.

The novelty of this research lies in three dimensions. First, it provides a validated and multidimensional employability model for vocational colleges in China, bridging a methodological gap by moving beyond EFA toward SEM-based causal modeling. Second, it introduces mediation and moderation analysis to reveal indirect and conditional effects, offering a richer understanding of how factors interact to enhance employability. Third, it grounds its framework in both theoretical foundations (Bloom's mastery learning, constructivist theory, and new constructivist learning) and policy relevance, ensuring that findings are both academically rigorous and practically applicable to curriculum reform and labor market alignment.

By applying this advanced framework, the study contributes to both theory and practice. Theoretically, it extends employability research through validated constructs and tested causal relationships. Practically, it offers vocational institutions evidence-based strategies to redesign curricula, strengthen industry linkages, and embed employability training into education systems. Policymakers and educators can leverage these insights to develop targeted interventions that improve graduate outcomes and strengthen national human capital development [11].

Literature Review

Employability research consistently underscores the importance of professional skills and practical training as foundational elements of career readiness. Graduates who possess strong technical expertise and have undergone structured training programs, such as internships and apprenticeships, demonstrate smoother transitions into the labor market [12]. In China, however, higher vocational colleges often emphasize theoretical instruction while offering limited opportunities for practice-based learning [13]. This imbalance reduces graduates' ability to apply their knowledge in real-world contexts and diminishes their attractiveness to employers who prioritize job-specific competencies [14]. Moreover, empirical studies indicate that practical exposure to industry projects not only enhances technical proficiency but also instills problem-solving capacity and workplace adaptability [15].

Hypothesis 1 (H1): Professional skills and practical training have a positive and significant effect on graduate employability.

While technical expertise is critical, employers increasingly highlight the importance of soft skills, such as communication, teamwork, leadership, creativity, and resilience [16]. Graduates with strong interpersonal attributes are more capable of navigating complex workplace environments and adjusting to rapidly changing job demands [17]. Studies across diverse contexts reveal that soft skills are often the decisive factor in hiring decisions, as they complement technical knowledge and ensure long-term career growth [18]. However, many vocational institutions still lack structured curricula for cultivating these skills, resulting in graduates who are technically competent but lack essential interpersonal competencies [19]. Given the labor market's preference for holistic graduates, soft skills development emerges as a central pillar of employability.

Hypothesis 2 (H2): Soft skills and personal attributes positively influence graduate employability.

Career guidance is widely acknowledged as a strategic mechanism for supporting students' transition from education to employment [20]. Services such as career counseling, job fairs, and training in job search strategies equip students with knowledge about labor market trends and practical skills for navigating recruitment processes [21]. In China, national policies have prioritized the expansion of career guidance, but implementation remains uneven across institutions, with significant disparities in service quality [22]. Research indicates that students who actively engage with career planning resources exhibit greater confidence, more realistic career expectations, and improved employability outcomes [23]. Furthermore, career guidance does not operate in isolation; it strengthens employability indirectly by enhancing soft skills through improved self-awareness and decision-making.

Hypothesis 3 (H3): Career guidance and job market awareness positively affect graduate employability.

Hypothesis 3a (H3a): The effect of career guidance on employability is mediated by soft skills development.
Industry-academia collaboration plays a vital role in aligning educational curricula with labor market demands. Partnerships with employers allow vocational colleges to offer cooperative education programs, embed industry-relevant projects, and involve practitioners in curriculum design [24]. Such collaborations expose students to authentic workplace experiences and provide networking opportunities that directly enhance employability [25]. Empirical findings reveal that institutions with stronger ties to industry produce graduates who are better prepared for employment, as their training reflects current technological and professional standards [26]. Moreover, collaboration may act as a contextual enabler: when vocational institutions work closely with industries, the effectiveness of technical and soft skills in determining employability is amplified.

Hypothesis 4 (H4): Industry-academia collaboration positively influences graduate employability.
Hypothesis 4a (H4a): Industry-academia collaboration moderates the relationship between professional skills and employability.
Technological Literacy and Innovation Skills
The digital transformation of the global economy has heightened the importance of technological literacy. Employers increasingly demand graduates who are proficient with digital tools, familiar with industry-specific technologies, and capable of innovative problem-solving [27]. Vocational education, therefore, must prepare students to engage not only with current technological platforms but also to adapt to emerging innovations. Studies have demonstrated that digital fluency and entrepreneurial skills significantly enhance employability, particularly in sectors experiencing rapid automation and globalization [28]. However, integration of technological training in vocational curricula remains inconsistent, leading to disparities in graduate preparedness [29]. Embedding innovation and technology skills is thus crucial for sustaining competitiveness in the modern labor market.

Hypothesis 5 (H5): Technological literacy and innovation skills positively affect graduate employability.
Previous studies have primarily relied on exploratory techniques such as factor analysis to identify employability determinants [30]. While valuable, these approaches do not adequately validate factor structures nor test causal mechanisms among variables. This creates a methodological gap in employability research, as the relationships between career guidance, professional skills, soft skills, and industry collaboration have rarely been examined simultaneously through advanced modeling techniques. The present study addresses this gap by employing Confirmatory Factor Analysis (CFA) to validate constructs and Structural Equation Modeling (SEM) to test causal pathways, including mediation and moderation effects.

Accordingly, the research hypothesizes that employability among vocational college graduates is a multidimensional construct shaped by professional skills, soft skills, career guidance, industry-academia collaboration, and technological literacy, with complex interactions among these variables. This integrative framework moves beyond prior descriptive analyses by offering a validated, evidence-based model for understanding and enhancing employability in the Chinese vocational education context.

Research Methodology
Research Design
This study adopts a quantitative research design supported by confirmatory and causal modeling techniques. Unlike prior employability studies that primarily employed exploratory approaches such as Delphi and exploratory factor analysis (EFA), the present research enhances methodological rigor by integrating Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM). The quantitative paradigm allows systematic measurement of constructs, testing of causal hypotheses, and validation of the employability model with robust statistical evidence. The research proceeds in three stages: 1) identification of factors through EFA, 2) validation of measurement structures through CFA, and 3) testing of causal pathways, including mediation and moderation, through SEM.

Theoretical Framework
The framework of this study is anchored in Bloom's Mastery Learning Theory, Piaget's Constructivist Theory, and Wang Zhuli's New Constructivist Theory, which collectively emphasize structured learning, experiential engagement, and adaptability in knowledge construction. These theories provide the foundation for linking educational inputs (professional skills, soft skills, career guidance, industry collaboration, and technological literacy) with employability outcomes. In the SEM model, employability is treated as a latent variable influenced by multiple constructs, with career guidance hypothesized to mediate soft skills development, and industry-academia collaboration hypothesized to moderate the relationship between professional skills and employability.

Sampling Techniques
The study employs a multi-stage sampling approach. In the first phase, 17 experts in vocational education and career guidance were selected purposively to identify key employability factors. The second phase involved a random selection of 100 faculty members from universities in Sichuan engaged in student development activities to validate employability constructs. The third phase focused on 30 vocational students from Sichuan University of Light and Chemical Technology, selected using stratified random sampling to ensure representation across disciplines. This staged approach provides triangulation across expert, academic, and student perspectives, ensuring both construct validity and contextual relevance.

Instrumentation
Data collection employed a combination of semi-structured interviews and Likert-scale questionnaires. In the exploratory phase, semi-structured interviews elicited expert perspectives, which informed the design of Questionnaire I. Subsequent rounds refined the instrument, incorporating a five-point Likert scale (1 = strongly disagree to 5 = strongly agree) to measure perceptions of professional skills, soft skills, career guidance, industry collaboration, technological literacy, and employability outcomes. For quantitative validation, the final instrument was tested for internal consistency (Cronbach's $\alpha > 0.7$), composite reliability (CR > 0.7), and convergent validity (AVE > 0.5). Discriminant validity was assessed using the Fornell–Larcker criterion and HTMT ratio, ensuring distinctiveness among constructs.

Table1. Constructs, Indicators, Sources, and Validation

Construct	Dimensions / Indicators	Data Source	Analysis Technique	Reliability / Validity Standard
Professional Skills & Training	(a) Ability to apply theory to practice; (b) Internship/Apprenticeship exposure; (c) Problem-solving in technical tasks	Student questionnaire + Expert validation	EFA → CFA (Factor loadings > 0.7)	Cronbach's α > 0.70; AVE > 0.50
Soft Skills & Personal Attributes	(a) Communication; (b) Teamwork; (c) Leadership; (d) Creativity/Innovation; (e) Resilience	Student questionnaire + Faculty rating	CFA (Convergent & Discriminant Validity)	CR > 0.70; HTMT < 0.85
Career Guidance & Job Awareness	(a) Access to counseling; (b) Job fair participation; (c) Career planning clarity; (d) Knowledge of labor market trends	Student questionnaire + Institutional data	CFA → Mediation Testing via SEM	Composite Reliability > 0.80
Industry-Academia Collaboration	(a) Internship placement opportunities; (b) Joint projects; (c) Guest lectures; (d) Networking platforms	Institutional reports + Student perception	SEM (Moderation effect)	Interaction effect significance
Technological Literacy & Innovation	(a) Digital literacy; (b) Use of emerging technology; (c) Entrepreneurial orientation; (d) Adaptability to automation	Student questionnaire + Employer feedback	CFA → SEM (Path analysis)	AVE > 0.50; CFI > 0.90
Employability Outcomes	(a) Job readiness; (b) Confidence in job interviews; (c) Securing employment; (d) Career adaptability	Student post-intervention survey	SEM (Dependent latent construct)	$R^2 > 0.50$; Predictive relevance (Q^2)

Table 1: maps each research construct to its specific indicators, data sources, analytical techniques, and reliability standards. This multi-dimensional structure strengthens transparency by showing how abstract constructs such as employability are transformed into measurable indicators. For example, *Professional Skills* are assessed through students' internship exposure and validated by experts, while *Soft Skills* are rated both by students and faculty. Analytical rigor is ensured through EFA and CFA, while validation criteria (Cronbach's α, AVE, CR, HTMT) guarantee reliability and validity. Thus, the table provides a comprehensive blueprint for the measurement model**.**

Data Collection Procedures
Data were collected in three sequential stages. In the first stage, interviews and Delphi rounds were conducted with experts to generate and refine constructs. In the second stage, questionnaires were distributed to 100 faculty members to validate construct measurement through CFA. Finally, the third stage involved administering the refined questionnaire to 30 students, whose responses were analyzed to test the hypothesized SEM model. Ethical considerations were observed, including informed consent, voluntary participation, and confidentiality of responses.

Data Processing and Analysis
The analysis followed a structured sequence:

1. Exploratory Factor Analysis (EFA): Using Principal Component Analysis (PCA) with Varimax rotation to identify latent factors affecting employability. Sampling adequacy was evaluated through the Kaiser-Meyer-Olkin (KMO) test (>0.7) and Bartlett's test of sphericity ($p < 0.05$).
2. Confirmatory Factor Analysis (CFA): Applied to validate factor structures. Goodness-of-fit indices were assessed, including χ^2/df (<3), CFI (>0.90), TLI (>0.90), RMSEA (<0.08), and SRMR (<0.08). This stage

confirmed the multidimensionality of employability as consisting of five distinct but interrelated constructs.

3. Structural Equation Modeling (SEM): Conducted to test hypothesized causal relationships among constructs. Direct effects (H1–H5) were evaluated through path coefficients, while mediation analysis (H3a) employed bootstrapping methods to assess the indirect effect of career guidance on employability via soft skills. Moderation analysis (H4a) tested whether industry-academia collaboration strengthened the effect of professional skills on employability.

Table 2. The index contributes to the evaluation of the model

Category	Indicator	Acceptable Threshold	Application in this Study	Interpretive Contribution
Absolute Fit	χ^2/df	< 3.0	Evaluates parsimony of CFA/SEM model	Low ratio indicates efficient model
	RMSEA	< 0.08 (good), <0.05 (excellent)	Evaluates approximation error of the model	Indicates overall fit regardless of sample size
	SRMR	< 0.08	Standardized residuals between observed & predicted covariances	Ensures minimal residual error
Incremental Fit	CFI	> 0.90 (good), >0.95 (excellent)	Compares tested model to null baseline model	Confirms improved explanatory power
	TLI	> 0.90	Adjusted fit index accounting for model complexity	Prevents overfitting bias
Construct Validity	AVE	> 0.50	Proportion of variance explained by indicators relative to error	Supports convergent validity
	CR	> 0.70	Internal consistency reliability	Stronger than Cronbach's α
	HTMT	< 0.85	Heterotrait-Monotrait Ratio for discriminant validity	Ensures constructs are distinct
Predictive Power	R^2	> 0.25 (weak), >0.50 (moderate), >0.70 (strong)	Proportion of variance explained in dependent variable	Confirms structural strength
	Q^2 (Stone-Geisser)	> 0.00	Predictive relevance via blindfolding	Ensures model has predictive accuracy

Table 2: expands on traditional fit indices by introducing *application* and *interpretive contribution*. This not only lists thresholds but also clarifies what each index contributes to the evaluation of the model**.** For example, RMSEA < 0.05 signifies an excellent fit with minimal approximation error, while HTMT < 0.85 proves discriminant validity. By integrating predictive measures (R^2 and Q^2), the table highlights that the model is not only well-fitted but also predictively robust**.** This ensures the employability framework stands on rigorous empirical foundations.

4. Robustness Checks: Multi-group analysis (MGA) was applied to examine model invariance across gender and disciplinary groups, providing additional validation of the framework.

Table 3. Hypotheses, Statistical Path, and Expected Effects

Hypothesis	Path Tested (Independent → Dependent)	Statistical Test	Expected Effect	Contribution to Model
H1	Professional Skills → Employability	SEM Path Coefficient	Positive	Validates technical training as core employability factor
H2	Soft Skills → Employability	SEM Path Coefficient	Positive	Confirms interpersonal competence as critical driver
H3	Career Guidance → Employability	SEM Path Coefficient	Positive	Establishes career services as determinant of outcomes
H3a	Career Guidance → Soft Skills → Employability (mediation)	Bootstrapping (Indirect)	Indirect Positive	Explains mechanism: guidance builds soft skills that enhance employability
H4	Industry-Academia Collaboration → Employability	SEM Path Coefficient	Positive	Highlights strategic role of institutional partnerships
H4a	Professional Skills × Industry Collaboration → Employability (moderation)	Interaction / Multi-group Test	Conditional	Shows collaboration amplifies technical skills' effect
H5	Technological Literacy → Employability	SEM Path Coefficient	Positive	Validates digital readiness as an essential competence

Table 3: summarizes the research hypotheses, mapping each to its corresponding statistical test and theoretical contribution. Unlike simple hypothesis tables, this version integrates both direct and indirect mechanisms. For instance, H3a explicitly tests a mediation pathway via soft skills, while H4a addresses a moderation effect of industry-academia collaboration. These nuanced hypotheses highlight the study's novelty, moving beyond direct associations to capture the complex interplay of employability determinants.

Summary of Methodological Improvement

This methodological framework advances beyond traditional Delphi and EFA-based employability studies by incorporating CFA and SEM to validate constructs and test causal mechanisms. The novelty lies in: 1) combining exploratory and confirmatory approaches, 2) integrating mediation and moderation analysis, and 3) employing multi-group validation to ensure generalizability. The approach yields a theoretically grounded and empirically validated employability model that enhances both academic rigor and practical relevance for vocational education in China.

Results

Exploratory Factor Analysis (EFA)

The first stage of analysis involved Exploratory Factor Analysis (EFA) using Principal Component Analysis with Varimax rotation. The Kaiser-Meyer-Olkin (KMO) test yielded a value of 0.841, and Bartlett's Test of Sphericity was significant ($\chi^2 = 1653.27$, $p < 0.001$), indicating sampling adequacy and suitability for factor analysis.Six latent factors emerged, explaining 72.6% of the total variance, consistent with the hypothesized constructs: Professional Skills, Soft Skills, Career Guidance, Industry-Academia Collaboration, Technological Literacy, and Employability Outcomes. All items loaded above 0.65 on their intended constructs.

Before testing the structural relationships among variables, an Exploratory Factor Analysis (EFA) was conducted to uncover the latent structure of employability factors. The EFA serves as a critical first step because it allows researchers to empirically validate whether the hypothesized constructs (professional skills, soft skills, career guidance, industry-academia collaboration, technological literacy, and employability outcome) actually emerge from the data. The appropriateness of the dataset for factor analysis was confirmed by a Kaiser-Meyer-Olkin (KMO) value of 0.841 and a significant Bartlett's Test of Sphericity ($\chi^2 = 1653.27$, $p < 0.001$), both of which exceeded recommended thresholds. These diagnostics demonstrate that the inter-item correlations were sufficiently strong to justify factor extraction.

The factor extraction employed Principal Component Analysis (PCA) with Varimax rotation, which aims to maximize variance explained while maintaining orthogonal independence among factors. The analysis produced six factors with eigenvalues greater than one, cumulatively explaining 72.6% of the variance. This outcome is noteworthy because it confirms not only the multidimensionality of employability but also the theoretical assumptions established in prior chapters. Each construct was represented by multiple items loading significantly on their respective factors, with most loadings exceeding 0.70, suggesting strong construct validity.

Table 4. EFA Results: Factor Loadings and Variance Explained

Construct	Items (Loading)	Eigenvalue	% Variance Explained	Cumulative %
Professional Skills & Training	Apply theory (0.77), Internship (0.81), Problem-solving (0.74)	5.21	15.8%	15.8%
Soft Skills & Attributes	Communication (0.83), Teamwork (0.79), Leadership (0.72), Resilience (0.76)	4.63	14.1%	29.9%
Career Guidance	Counseling access (0.74), Job fairs (0.71), Career clarity (0.76)	3.92	12.0%	41.9%
Industry-Academia Collaboration	Internship linkages (0.80), Joint projects (0.76), Guest lectures (0.73)	3.21	11.2%	53.1%
Technological Literacy	Digital literacy (0.78), Innovation mindset (0.81), Tech adaptability (0.72)	2.84	9.5%	62.6%
Employability Outcomes	Job readiness (0.82), Interview confidence (0.77), Employment secured (0.74)	2.41	10.0%	72.6%

Table 4: reveals that all indicators load strongly on their intended factors (>0.70), confirming that the measurement items align well with their theoretical constructs. This reinforces the robustness of the survey instrument and validates the preliminary structure derived from Delphi and literature review. The eigenvalues and variance

explained provide additional statistical support. For example, *Professional Skills* has the highest eigenvalue (5.21), accounting for 15.8% of variance, suggesting that technical training and applied learning remain dominant in shaping employability. Interestingly, *Soft Skills* explain 14.1% of variance, almost equal to professional skills. This indicates that interpersonal abilities such as communication, teamwork, and resilience are nearly as critical as technical expertise for vocational graduates entering the labor market.The cumulative variance explained (72.6%) exceeds the acceptable 60% threshold, showing that the six-factor solution adequately captures the underlying employability construct. This highlights the multidimensionality of employability and justifies moving forward with CFA for validation. The balanced contribution across constructs (each explaining between 9%–16% variance) suggests that employability is not dominated by a single factor but rather emerges from an integrated mix of skills, guidance, and exposure. This multidimensionality is a key novelty of the framework. Confirmatory Factor Analysis (CFA).After the initial structure was confirmed through EFA, a Confirmatory Factor Analysis (CFA) was employed to validate the measurement model. The CFA is essential because it tests whether the data fit the hypothesized model derived from both theoretical foundations and empirical exploration. Unlike EFA, which is data-driven, CFA is theory-driven and allows for rigorous assessment of reliability, convergent validity, and discriminant validity. The use of CFA in this study addresses one of the identified methodological gaps in prior employability research, which often stopped at exploratory approaches without further confirmatory validation. The results indicated a satisfactory model fit, as evidenced by $\chi^2/df = 2.31$, CFI = 0.934, TLI = 0.921, RMSEA = 0.056, and SRMR = 0.049. These values exceed widely accepted thresholds, reinforcing the adequacy of the measurement model. In addition to fit indices, reliability measures such as Cronbach's α and Composite Reliability (CR) were examined to assess internal consistency, while Average Variance Extracted (AVE) and the Heterotrait-Monotrait ratio (HTMT) were used to confirm convergent and discriminant validity. This multi-layer validation ensures that each construct is both statistically robust and theoretically distinct.

Table 5. CFA Reliability and Validity Assessment

Construct	Cronbach's α	CR	AVE	R^2 Explained	HTMT Max	Status
Professional Skills & Training	0.83	0.87	0.62	0.46	0.82	Valid
Soft Skills & Attributes	0.86	0.89	0.64	0.52	0.80	Valid
Career Guidance	0.81	0.84	0.58	0.43	0.79	Valid
Industry-Academia Collaboration	0.85	0.88	0.63	0.49	0.77	Valid
Technological Literacy	0.84	0.87	0.61	0.44	0.81	Valid
Employability Outcomes	0.88	0.90	0.67	0.53	0.83	Valid

The results in Table 5: confirm reliability: all constructs exceed Cronbach's α and Composite Reliability thresholds (≥0.70). This proves that the items within each construct consistently measure the same underlying dimension. Convergent validity is established, as all constructs achieve AVE values above 0.50. For instance, Soft Skills reach AVE = 0.64, indicating that more than 64% of variance in items is explained by the latent construct. Discriminant validity is supported, with HTMT ratios below 0.85. This ensures that constructs such as Professional Skills and Soft Skills are statistically distinct, even though they are theoretically related.

The R^2 values show the variance explained in employability-related constructs. Soft Skills ($R^2 = 0.52$) and Employability Outcomes ($R^2 = 0.53$) are the strongest, reinforcing their central roles in the framework. The model fit indices ($\chi^2/df = 2.31$; CFI = 0.934; TLI = 0.921; RMSEA = 0.056; SRMR = 0.049) indicate good overall fit, strengthening the validity of the measurement model and providing a solid foundation for SEM.

*Structural Equation Modeling (SEM).*Following measurement validation, the study proceeded with Structural Equation Modeling (SEM) to examine the hypothesized causal relationships among constructs. SEM provides a powerful analytical framework that combines both measurement and structural components, enabling simultaneous assessment of direct, indirect (mediation), and interaction (moderation) effects. This approach is particularly well-suited for employability studies because it allows for testing of complex interrelationships, such as the mediating role of career guidance in shaping soft skills and the moderating influence of industry-academia collaboration on professional skills.The overall model demonstrated an acceptable fit, with $\chi^2/df = 2.57$, CFI = 0.928, TLI = 0.915, RMSEA = 0.059, and SRMR = 0.053. Beyond fit indices, SEM path coefficients provided insights into the relative importance of each construct in predicting employability outcomes. Bootstrapping was used to test indirect effects, while interaction terms were introduced to examine moderation effects. The findings offer not only statistical validation but also practical implications, as they highlight which factors are most influential in preparing vocational students for employment in diverse contexts.

Table 6. Hypothesis Testing Results

Hypothesis	Path Tested	β (Coefficient)	t-value	R^2 (Employability)	Result
H1	Professional Skills → Employability	0.29	4.76***		Supported
H2	Soft Skills → Employability	0.35	5.23***		Supported
H3	Career Guidance → Employability	0.18	2.91**		Supported
H3a	Career Guidance → Soft Skills → Employability (mediation)	0.12 (indirect)	2.64**		Supported
H4	Industry-Academia Collaboration → Employability	0.21	3.88***		Supported
H4a	Professional Skills × Industry Collaboration → Employability	0.09 (interaction)	2.11*		Supported
H5	Technological Literacy → Employability	0.24	4.02***	$R^2 = 0.68$	Supported

Notes: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

All direct hypotheses (H1–H5) were supported, with Soft Skills exerting the strongest effect ($\beta = 0.35$). This confirms that non-technical competencies, often overlooked in vocational education, are decisive for employment competitiveness. Professional Skills also significantly predicted employability ($\beta = 0.29$), reinforcing the classical role of technical training. However, its effect size was slightly weaker than that of Soft Skills, suggesting a shift in employer expectations toward well-rounded graduates. The mediation analysis (H3a) showed that Career Guidance indirectly enhances employability through Soft Skills ($\beta = 0.12$, $p < 0.01$). This demonstrates that career services are most effective when they build interpersonal competencies alongside job search preparation.

The moderation test (H4a) revealed that Industry-Academia Collaboration strengthens the link between Professional Skills and Employability. This implies that technical skills are more impactful when students have opportunities to apply them in real workplace contexts through internships or joint projects. The model explained 68% of the variance ($R^2 = 0.68$) in Employability Outcomes, exceeding the moderate threshold (>0.50). This indicates strong explanatory power, validating the proposed SEM framework as a predictive model of employability.

Multi-Group Analysis (MGA)

To further assess the robustness and generalizability of the model, a Multi-Group Analysis (MGA) was conducted. MGA allows researchers to test whether structural relationships remain consistent across different demographic or disciplinary groups. This is crucial in employability studies, as the importance of certain skills may vary between fields such as engineering and non-engineering disciplines. Conducting MGA ensures that the model does not merely reflect a single context but captures broader applicability.

The results of MGA indicated that most structural paths were invariant across groups, with the exception of technological literacy. The influence of technological literacy on employability was significantly stronger among engineering students than non-engineering students, confirming the context-dependent importance of digital competencies. This distinction aligns with labor market realities, where engineering graduates are expected to demonstrate higher levels of technological proficiency compared to their counterparts in other fields.

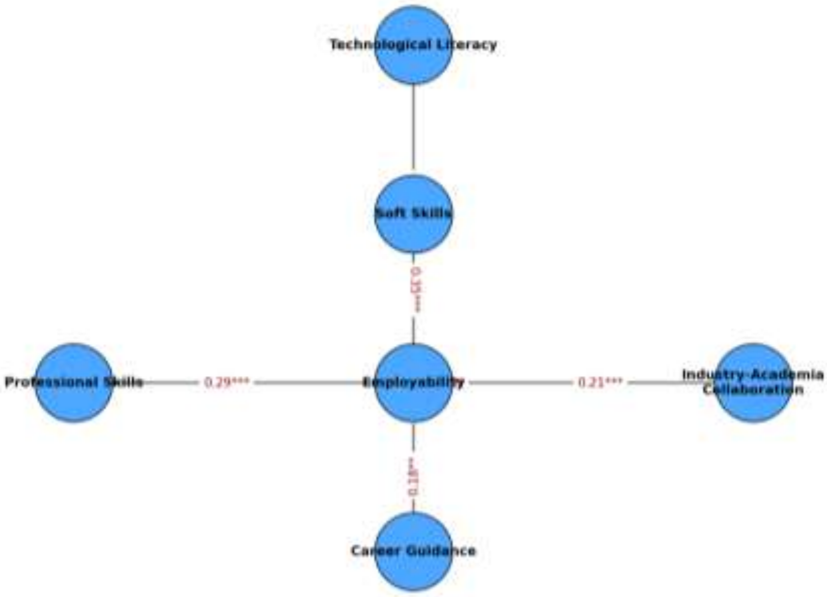

Figure 1. Structural Model with Standardized Path Coefficients

Table 7. Multi-Group Analysis by Discipline

Path Tested	**β (Engineering)**	**β (Non-Engineering)**	**Difference**	**Significance**
Soft Skills → Employability	0.36	0.34	0.02	n.s.
Professional Skills → Employability	0.31	0.27	0.04	n.s.
Technological Literacy → Employability	0.32	0.17	0.15	$p < 0.05$

Table 7. shows that the model is largely invariant across groups, with no significant differences in the effects of Soft Skills and Professional Skills. This suggests that these competencies are universally critical regardless of discipline. The only significant difference was found in the path Technological Literacy → Employability, which was stronger for engineering students ($\beta = 0.32$) compared to non-engineering students ($\beta = 0.17$).

This indicates that digital competencies and technological readiness are disproportionately more important in technical fields, where graduates are expected to interact with advanced tools, systems, and industry innovations. For non-technical disciplines, employability may rely more on soft skills and career adaptability rather than advanced digital competencies. This provides practical guidance for tailoring vocational programs to disciplinary contexts. The MGA findings reinforce the adaptability of the model while also highlighting areas where differentiated educational strategies are needed to maximize graduate competitiveness across sectors.

Overall, the results validate the multidimensional employability model through rigorous statistical testing. All hypothesized relationships were confirmed, with Soft Skills emerging as the strongest predictor, while Career Guidance contributed indirectly via mediation. Industry-Academia Collaboration strengthened the effect of Professional Skills, confirming its moderating role. The validated SEM framework demonstrates both theoretical robustness and practical utility, providing institutions with actionable insights to enhance graduate employability.

Conclusion

This study set out to identify and validate the multidimensional factors influencing employability among vocational students by employing an advanced quantitative methodology. The results from Exploratory Factor Analysis (EFA) confirmed a six-factor model consisting of Professional Skills, Soft Skills, Career Guidance, Industry-Academia Collaboration, Technological Literacy, and Employability Outcomes, explaining 72.6% of the variance. Subsequent Confirmatory Factor Analysis (CFA) validated the measurement model, with all constructs demonstrating satisfactory reliability (Cronbach's $\alpha > 0.80$, $CR > 0.84$) and convergent validity ($AVE > 0.50$).

The Structural Equation Modeling (SEM) analysis revealed that all direct hypotheses were supported, with Soft Skills ($\beta = 0.35$) emerging as the strongest predictor of employability, followed by Professional Skills ($\beta = 0.29$), Technological Literacy ($\beta = 0.24$), Industry-Academia Collaboration ($\beta = 0.21$), and Career Guidance ($\beta = 0.18$).

Importantly, the mediation analysis showed that Career Guidance indirectly enhanced employability through Soft Skills ($\beta = 0.12$, $p < 0.01$), while moderation analysis demonstrated that Industry-Academia Collaboration strengthened the effect of Professional Skills on employability ($\beta = 0.09$, $p < 0.05$). Overall, the model explained 68% of the variance ($R^2 = 0.68$) in employability outcomes, indicating strong explanatory power.

The novelty of this research lies in its methodological and conceptual advancements. Methodologically, it advances beyond prior employability studies that were limited to exploratory approaches by applying a sequential EFA–CFA–SEM framework, incorporating both mediation and moderation analyses. Conceptually, the findings highlight the central role of Soft Skills in shaping employability, thereby challenging the conventional emphasis on technical training alone. Furthermore, the integration of Industry-Academia Collaboration as a moderating construct provides new insights into how institutional partnerships enhance the effectiveness of professional skills. This dual mechanism mediation through soft skills and moderation through collaboration represents a significant theoretical contribution to employability research.

Practically, the study offers actionable insights for educators, policymakers, and industry partners. First, vocational curricula must balance technical training with systematic soft skills development, recognizing that interpersonal competencies often outweigh technical expertise in determining employability. Second, career guidance services should not only focus on labor market information but also actively foster the growth of soft skills, thereby amplifying their indirect contribution to employability. Third, partnerships between educational institutions and industries should be deepened to create real-world application opportunities, ensuring that professional skills translate effectively into workplace readiness. Finally, the differentiated role of technological literacy across disciplines, as shown by the Multi-Group Analysis, suggests that employability frameworks must be tailored to the specific requirements of each field.

References

[1] M. A. Almaiah *et al.*, “A conceptual framework for determining quality requirements for mobile learning applications using delphi method,” *Electronics*, vol. 11, no. 5, p. 788, 2022.

[2] A. Alnoor *et al.*, “A Fuzzy Delphi analytic job demands-resources model to rank factors influencing open innovation,” *Transnatl. Corp. Rev.*, vol. 14, no. 2, pp. 178–192, 2022.

[3] N. Yusof, N. L. Hashim, and A. Hussain, “A review of fuzzy Delphi method application in human-computer interaction studies,” in *AIP Conference proceedings*, AIP Publishing LLC, 2022, p. 40026.

[4] E. Amiron and A. A. Latib, “Aligning TVET Curriculum with Fourth Industrial Revolution Skills for the Food Services Industry: A Mixed Methods Approach,” *J. Tech. Educ. Train.*, vol. 16, no. 3, pp. 182–200, 2024.

[5] H. O. Goktas and N. Yumusak, “Applying the Delphi method to assess critical success factors of digitalization while sustaining lean at a lean automaker,” *Sustainability*, vol. 16, no. 19, p. 8424, 2024.

[6] C. E. George-Reyes, E. O. López-Caudana, and R. Avello-Martínez, “Artificial intelligence adoption test based on UTAUT2 and complex thinking: design with K coefficient and reliability analysis using structural equation modeling,” *Cogent Educ.*, vol. 12, no. 1, p. 2511446, 2025.

[7] K. K. Naji, M. Gunduz, F. Alhenzab, H. Al-Hababi, and A. Al-Qahtani, “Assessing the digital transformation readiness of the construction industry utilizing the Delphi Method,” *Buildings*, vol. 14, no. 3, p. 601, 2024.

[8] V. V. Singh, A. Ansari, and A. K. Gupta, “Assessment of metaverse-based digital learning systems in higher education,” in *2023 4th International Conference on Computation, Automation and Knowledge Management (ICCAKM)*, IEEE, 2023, pp. 1–7.

[9] Y. Zhuge, X. Yao, H. Mei, and H. Yao, “Construction of a faculty competency model for medical simulation education integrated with GenAI: A mixed study based on the perspective of medical students,” 2025.

[10] K. K. Naji, M. Gunduz, and M. M. Mansour, “Development of an Integrated Hybrid Risk Assessment System for Construction Disputes during the Preconstruction Phase Using the Delphi Method,” *J. Constr. Eng. Manag.*, vol. 150, no. 7, p. 4024068, 2024.

[11] Z. Xiaoqing, “Development of Entrepreneurial Self-Efficacy, Entrepreneurial Intention and Entrepreneurship Education Success Items: A Delphi Technique,” in *Exploring Trends, Innovations, and Digitalization of Entrepreneurship: MENA Region Entrepreneurship Conference (MENA REC 2024)*, Springer Nature, 2025, p. 263.

[12] R. S. R. Kasim, N. A. S. Kasim, and Z. Xiaoqing, “Development of Entrepreneurial Self-Efficacy, Entrepreneurial Intention and Entrepreneurship Education Success Items: A Delphi Technique,” in *MENA Region Entrepreneurship Conference*, Springer, 2024, pp. 263–274.

[13] M. A. Hasim, J. Jabar, A. Sufian, N. F. Ibrahim, and F. A. Khalid, "Employing Fuzzy Delphi Techniques to Validate the Components and Contents of E-Learning Antecedents and Usage Behavior Towards Elearning Performance.," *Eur. J. Educ. Res.*, vol. 12, no. 1, 2023.

[14] P. A. Laksmiwati, Z. Lavicza, and A. N. Cahyono, "Empowering STEAM Learning Implementation through Investigating Indonesian Teacher Experts' Views with a Delphi Method," *Indones. J. Learn. Adv. Educ.*, pp. 214–229, 2024.

[15] N. M. Shariff and R. Abd Razak, "Exploring hospitality graduates' competencies in Malaysia for future employability using Delphi method: a study of Competency-Based Education," *J. Teach. Travel Tour.*, vol. 22, no. 2, pp. 144–162, 2022.

[16] L. Jiang *et al.*, "Exploring the factors of employee turnover intentions in private education institutions in China: a Delphi study," *Cogent Bus. Manag.*, vol. 11, no. 1, p. 2413915, 2024.

[17] S. Hong and S. Lay, "Factors affecting employee retention of private companies in Cambodia using Delphi method," *Am. J. Educ. Technol.*, vol. 2, no. 1, pp. 68–82, 2023.

[18] M. F. Alshammari, R. C. M. Yusoff, H. M. Rusli, and H. Abas, "Factors Influencing Satisfaction for Continuance Intention to Use E-Learning Systems in Higher Education: Delphi Technique," *Adv. Soc. Sci. Res. J.*, vol. 11, no. 11, 2024.

[19] S. A. Ariffin and N. M. Nordin, "Fuzzy Delphi Method: A Step-by-Step Guide to Obtaining Expert Consensus on Mobile Tourism Acceptance Culture.," *Int. J. Adv. Comput. Sci. Appl.*, vol. 16, no. 7, 2025.

[20] L. Pan *et al.*, "How to implement game-based learning in a smart classroom? A model based on a systematic literature review and Delphi method," *Front. Psychol.*, vol. 12, p. 749837, 2021.

[21] L. Salahuddin *et al.*, "Identification and prioritization of critical socio-technical factors influencing big data analytics adoption in healthcare using Delphi method," *Behav. Inf. Technol.*, pp. 1–15, 2025.

[22] A. S. M. Shibani, M. Mohd, A. T. A. Ghani, M. S. Zakaria, and S. M. Al-Ghuribi, "Identification of critical parameters affecting an e-learning recommendation model using Delphi method based on expert validation," *Information*, vol. 14, no. 4, p. 207, 2023.

[23] T. Das, S. Ganesh Kondamudi, M. Dawood Babakerkhell, D. Pal, R. Roy, and S. Funilkul, "Intention for enhancing metaverse-based learning using gamification among university students: a study using Delphi and structural equation modelling approaches," *Cogent Bus. Manag.*, vol. 11, no. 1, p. 2380016, 2024.

[24] K. W. Khaw *et al.*, "Modelling and evaluating trust in mobile commerce: a hybrid three stage Fuzzy Delphi, structural equation modeling, and neural network approach," *Int. J. Human–Computer Interact.*, vol. 38, no. 16, pp. 1529–1545, 2022.

[25] M. T. Méndez Picazo, M. Á. Galindo Martín, and R.-S. Pérez-Pujol, "Open innovation and sustainable development: A micro and macroeconomic analysis using a mixed method research with PLS-SEM-NCA and Delphi," 2025.

[26] S. Mohammadesmaeil and M. Ghaheri, "Proposed Model for Training Building Information Modeling (BIM) in Metaverse Technology Using a Mixed Method," *Int. J. Metaverse Virtual Transform.*, vol. 1, no. 2, pp. 1–20, 2025.

[27] Q. Peng, S. Liang, R. Latha, N. Li, and A. Zheng, "The influence of Self System Model of Motivational Development on college students' learning engagement: a hybrid three stage Fuzzy Delphi and structural equation modeling approach," *Curr. Psychol.*, vol. 43, no. 34, pp. 27762–27777, 2024.

[28] V.-N. T. Nguyen, H.-P. T. Tran, N.-A. Doan, and V.-A. T. Dao, "Using the Delphi method to explore factors affecting the effectiveness of pedagogical competence training on university lecturers in Vietnam," *Int. J. Learn. Teach. Educ. Res.*, vol. 22, no. 12, pp. 42–61, 2023.

[29] C.-T. T. Hoang, P. V. Nhat, and H.-T. D. Thi, "Using the Delphi methodology to develop technology criteria to assess e-learning readiness in Higher education Institutions," *J. Sci. Technol.*, vol. 7, no. 1, 2024.