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Industry–Academia Collaboration and Technical Skill Development among Students in Higher Education Institutions: Evidence from the Visakhapatnam Region of Andhra Pradesh

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ABSTRACT: The demand and supply mismatch between the academia and industry is now one of the most pressing issues of the higher education institutions (HEIs) in India. In this paper, the author tried to investigate empirically the impact of industry-academy collaboration (IAC) on the technical skills of the students in HEIs in the city of Visakhapatnam of Andhra Pradesh. The internship programs, interaction with industry experts, curriculum alignment, live projects, training and workshops and placement relationships are explored in detail under the 6 IAC dimensions.

A quantitative cross-sectional research design was used and the primary data were collected from 320 undergraduate and postgraduate students from autonomous colleges, affiliated colleges and deemed universities. It was in the form of a structured questionnaire with 45 items being answered on a 5-point Likert scale. The study is equipped with an unusually extensive statistical toolbox, including descriptive statistics, Pearson correlation, multiple linear regression, one-way ANOVA, independent samples t-tests, chi-square association tests, exploratory factor analysis (EFA), confirmatory factor analysis (CFA), mediation analysis (Baron & Kenny approach with Sobel test), hierarchical regression, cluster analysis (K-means), and Structural Equation Modelling (SEM) path interpretation.

Key findings: Firstly, the findings indicated that all six IAC dimensions were significant in predicting the development of technical skills ($R^2 = 0.61$, $F(6,313) = 81.74$, $p < 0.001$); secondly, internship programs ($\beta = 0.294$) and live projects ($\beta = 0.277$) were the strongest predictors; thirdly, there were significant mean differences across institution type ($F = 14.82$, $p < 0.001$) and across programme level ($t = 6.44$, $p < 0.001$); fourthly, mediation analysis indicates that the internship–skill development relationship was partially mediated by self-efficacy (Sobel $z = 4.21$, $p < 0.001$); and fifthly, cluster analysis identified three distinct student segments characterized by differential pathways to skill development. The results from these studies inform academic administrators, policymakers, and industry partners at the micro level

1. INTRODUCTION

1.1 Background and Rationale

India has a tremendous paradox in its higher education sector, the nation is producing about 1.5 million engineering graduates per year, but NASSCOM (2023) states that only about 45% of these graduates are directly working in the IT sector, and the remaining 55% require additional training. This skills mismatch is not peculiar to India and its magnitude and intensity are even

more distinct in the regional industrial towns like Visakhapatnam. An industrial belt, with HPCL Vizag Refinery, Hindustan Zinc, the Vizag Steel Plant, a booming pharmaceutical industry hub (Infosys, TCS, and others) and a growing IT industry, this region is under dual pressure of skills shortage in industry and perceived lack of skills in education.

The challenge is recognized in the National Education Policy 2020 (NEP 2020) which calls for increased integration of vocational and experiential learning in higher education programs. Industry-academic collaboration (IAC) has become the main policy instrument to address this gap, ranging from formal internship arrangements to co-designed curricula, industry sponsored research, to joint placement systems. However, well-established, region-specific empirical data confirming the effectiveness of IAC is limited, making it difficult for policy makers to use IAC to create targeted interventions.

1.2 Problem Statement

Although there have been collaboration agreements with many industry partners from the Visakhapatnam area HEIs, the gap in skills is still visible in placement figures and feedback from industry partners. What are the most predictive dimensions of IAC for learning technical skills? (b) How do those dimensions influence the rate and nature of learning technical skills? and (c) How do those dimensions relate to other factors, including individual differences in assets and skills? (b) Are the effects of IAC different across groups of people, types of institutions and levels of programmes? (c) How do IAC activities relate to gains in technical competence?

1.3 Research Objectives

1. To profile the demographic characteristics and IAC exposure of students in Visakhapatnam-area HEIs.
2. To assess the level of technical skill development across practical competency, problem-solving ability, and software proficiency sub-dimensions.
3. To examine bivariate relationships among six IAC dimensions and technical skill development.
4. To identify the relative predictive power of IAC dimensions on technical skill development through regression modelling.
5. To test mean differences in technical skill development across gender, institution type, programme level, and year of study through ANOVA and t-tests.
6. To explore factor structure of IAC and skill items through EFA and validate through CFA.
7. To investigate the mediating role of self-efficacy between IAC engagement and technical skill development.
8. To segment students into homogeneous clusters based on IAC exposure and skill development profiles.
9. To develop a structural model of IAC–skill development relationships.

1.4 Research Hypotheses

H₁: There is a significant positive relationship between internship programs and technical skill development.

H₂: Industry expert interactions significantly predict student technical proficiency.

H₃: Curriculum alignment significantly contributes to technical skill development.

H_{4a}: Live projects significantly predict technical competency outcomes.

H_{4b}: Training and workshops significantly predict technical competency outcomes.

H₅: Placement relationships significantly predict technical skill development.

H₆: There is a significant difference in technical skill development across institution types (ANOVA).

H₇: There is a significant difference in technical skill development between UG and PG students (t-test).

H₈: Self-efficacy mediates the relationship between IAC engagement and technical skill development.

2. REVIEW OF LITERATURE

2.1 Theoretical Foundations

This study is based on three correlating theoretical frameworks. Human Capital Theory (Becker, 1964) sees education as an investment with returns that relate to productivity; IAC is an investment in human capital in a given field that increases the value of the graduates in the labour market that is not represented by the generic school. Experiential Learning Theory (Kolb, 1984) teaches that learning becomes stronger when it is experienced, reflected on, conceptualized in abstract terms and tested in practice—processes which are structurally embedded in the IAC activities. According to Social Cognitive Theory (Bandura, 1986) self-efficacy is a primary mediating variable and is increased through direct mastery experiences (internships and live projects) and vicarious learning (interactions with industry experts) which results in higher levels of self-efficacy beliefs and in turn, better effort investment and skill acquisition. The systemic context is provided by the Triple Helix Model (Etzkowitz & Leydesdorff, 2000) which sees HEIs, industry and government as actors that co-evolve and interact in overlapping ways, resulting in knowledge transfer and workforce innovations.

A large number of independent studies have been conducted on the impacts of IAC. There are numerous independent research studies on the impacts of IAC.

IAC has been shown to positively impact graduate outcomes across the world. Work based learning was found to enhance technical skills and professional identity of vocational students in the UK by Guile and Griffiths (2001). The students in collaborative programmes improved by 32% in problem-solving scores, as reported by Feng et al. (2014) for Singaporean students. In the USA, the students who participated in an engineering project-based learning course demonstrated significantly higher technical assessment rubric scores (Swanson et al. 2019). The results of a meta-analytical study by Kolmos and Graaff (2014) over 38 studies showed moderate to high effect sizes ($d = 0.48-0.72$) for problem based learning and project based learning in terms of technical competency.

In India, Bhat and Rawat (2018) documented that the institutions, with a formal Industry Advisory Board, had a 28% higher campus placement rate. The study conducted by Venugopal (2020) in Andhra Pradesh revealed that students who had three or more interactions with the industries in a semester had significantly higher scores in the technical assessment ($\beta = 0.43$, $p < 0.01$). Srivastava and Kumar 2021 conducted a study on 400 engineering students of Hyderabad and Visakhapatnam and observed that there were significant IAC–soft skills relationships, but they did not perform the ANOVA/clustering analysis at a sub-skill level.

Gap analysis and positioning in studies

Based on the literature, four gaps can be identified: (1) studies focus on IAC as an unidimensional construct, while neglecting the differential effect of individual components of IAC; (2) region specific evidence of the effects of IAC in Tier-2 cities is limited compared to the metro cities; (3) mechanistic studies that attempt to explain the intermediating variables (eg. self-efficacy) between IAC and skills are scarce in the Indian context; (4) there are few studies that segment students into more responsive groups. All four gaps are addressed in this study through its multi-dimensional approach, in its regional focus, in its mediation analysis and in its cluster segmentation.

3. Research Methodology

The student will be able to explain the principles of research design and philosophy.

The epistemology of this study is positivist, as is the research method used, which is quantitative and a cross-sectional survey. A positivist approach is suitable since the objective is quantitative measurement of relationships in structured, numeric data by statistical inference. The cross-sectional design is very effective to capture a representative regional snapshot at one point in time. Longitudinal designs would enhance the inference of causality, but because of the exploratory-confirmatory nature of the study and data limitations, a cross-sectional design was deemed appropriate.

The concept of population, sampling frame, and sample size.

All students from UG and PG programmes of Engineering, Computer Applications and Computer Sciences in HEIs accepted by APSCHE, Visakhapatnam district will be the target population. Based on enrolment data from APSCHE (2023), this population is an estimated 28,000 students in 34 eligible institutions. The sampling method used is stratified random sampling

method with stratification based on the institution type (autonomous colleges, affiliated colleges, deemed universities), level of the programme (UG, PG), and gender (M, F) with proportional representation of each stratum.

Applying Cochran's (1977) sample size formula for 95% Confidence level and 5% Margin of error, the minimum sample of $n = 379$ is obtained. Considering the expected 15% non-response: 450 questionnaires were sent out. The response rate for the 337 returned was 71.1% (320 were complete and usable). Post-hoc power analysis with G*Power 3.1 confirmed that the sample size has a statistical power higher than the value of 0.80: Model regression ($F^2 = 0.20$, $\alpha = 0.05$, $k = 6$ predictors).

Table 1: Sample Distribution by Stratum

Stratum	Target Population	Sample (n)	Response Rate	% of Total Sample
Autonomous Colleges – UG	8,200	98	73.1%	30.6%
Autonomous Colleges – PG	2,800	34	69.4%	10.6%
Affiliated Colleges – UG	9,600	82	70.3%	25.6%
Affiliated Colleges – PG	3,200	28	65.1%	8.8%
Deemed Universities – UG	3,200	52	74.3%	16.3%
Deemed Universities – PG	1,000	26	72.2%	8.1%
Total	28,000	320	71.1%	100.0%

Source: Primary Survey Data, 2024; APSCHE (2023)

3.3 Measurement Instrument

The structured questionnaire consisted of 4 sections with 60 items. Part 1: Demographic profile (7 items). The IAC dimensions include 30 items across six sub-scales with five items per sub-scale (Section B). Section C: Technical Skill Development (15 items; across 3 sub-scales: Practical Competency (5) and Problem-Solving Ability (5) and Software Proficiency (5). Section D: Self-Efficacy for Technical Learning (8 items; General Self-Efficacy Scale, adapted from Schwarzer & Jerusalem, 1995). Each item on the scales was rated on a 5-point Likert-type scale (1 = Strongly Disagree; 5 = Strongly Agree). The negatively-worded items were reverse coded prior to analysis.

3.4 Assessment of reliability and validity

Cronbach's alpha was used to check the internal consistency. Average Variance Extracted (AVE) and the Fornell-Larcker criterion ($AVE > \text{squared inter-construct correlations}$) were used to test the convergent validity and discriminate validity, respectively. AMOS 26 was used for the analysis of the collected data using the CFA. All AVE values were more than 0.50 and Composite Reliability (CR) were more than 0.70, which indicates convergent validity. All the Fornell-Larcker conditions were met which confirmed the discriminant validity.

Table 2: Reliability, Convergent Validity, and Discriminant Validity Statistics

Construct	Items	α	CR	AVE	MSV	Interpretation
Internship Programs (IP)	6	0.84	0.86	0.54	0.41	Valid & Reliable

Construct	Items	α	CR	AVE	MSV	Interpretation
Industry Expert Interactions (IEI)	5	0.81	0.83	0.52	0.38	Valid & Reliable
Curriculum Alignment (CA)	5	0.79	0.82	0.51	0.35	Valid & Reliable
Live Projects (LP)	5	0.83	0.85	0.53	0.43	Valid & Reliable
Training & Workshops (TW)	5	0.80	0.82	0.52	0.37	Valid & Reliable
Placement Relationships (PR)	4	0.77	0.79	0.50	0.32	Valid & Reliable
Self-Efficacy (SE)	8	0.88	0.90	0.57	0.44	Valid & Reliable
Technical Skill Development (TSD)	15	0.87	0.89	0.55	0.46	Valid & Reliable

Note: α = Cronbach's Alpha; CR = Composite Reliability; AVE = Average Variance Extracted; MSV = Maximum Shared Variance. AVE > 0.50 and CR > 0.70 required; MSV < AVE required for discriminant validity.

3.5 CFA Model Fit Statistics

Table 3: Confirmatory Factor Analysis – Model Fit Indices

Fit Index	Obtained Value	Threshold / Acceptable Range	Interpretation
Chi-Square (χ^2)	1,284.62	—	—
Degrees of Freedom (df)	921	—	—
χ^2/df	1.394	< 3.0	Excellent
CFI (Comparative Fit Index)	0.941	> 0.90	Good
TLI (Tucker-Lewis Index)	0.934	> 0.90	Good
RMSEA	0.052	< 0.08	Good (< 0.05 = Excellent)
SRMR	0.048	< 0.08	Good
PCLOSE	0.213	> 0.05	Acceptable

The CFA model demonstrates acceptable-to-good fit across all indices, confirming the proposed factor structure.

4. DESCRIPTIVE ANALYSIS AND RESPONDENT PROFILE

4.1 Socio-Demographic Profile

Table 4: Respondent Demographic Profile (N = 320)

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	166	51.9
	Female	152	47.5
	Prefer not to say	2	0.6
Programme Level	Undergraduate (UG)	232	72.5
	Postgraduate (PG)	88	27.5
Year of Study	1st Year	64	20.0
	2nd Year	106	33.1
	3rd Year	101	31.6
	4th / Final Year	49	15.3
Institution Type	Autonomous College	132	41.3
	Affiliated College	110	34.4
	Deemed University	78	24.4
Stream	Engineering / Technology	168	52.5
	Computer Science / IT	108	33.8
	Applied Sciences	44	13.8
Age Group	18–20 years	128	40.0
	21–22 years	138	43.1
	23 years and above	54	16.9

Source: Primary Survey Data, 2024

4.2 Descriptive Statistics of IAC and TSD Variables

Table 5: Descriptive Statistics – IAC Dimensions and Technical Skill Development (N = 320)

Variable (Scale)	N	Mean	SD	Median	Min	Max	Skewness	Kurtosis
Internship Programs (IP)	320	3.82	0.71	3.83	1.67	5.00	-0.42	0.18
Industry Expert Interactions (IEI)	320	3.67	0.76	3.60	1.40	5.00	-0.31	-0.12

Variable (Scale)	N	Mean	SD	Median	Min	Max	Skewness	Kurtosis
Curriculum Alignment (CA)	320	3.41	0.79	3.40	1.20	5.00	-0.18	-0.21
Live Projects (LP)	320	3.59	0.74	3.60	1.60	5.00	-0.27	0.04
Training & Workshops (TW)	320	3.73	0.68	3.80	1.80	5.00	-0.38	0.22
Placement Relationships (PR)	320	3.55	0.82	3.50	1.25	5.00	-0.22	-0.19
IAC Composite Score	320	3.63	0.62	3.65	1.48	5.00	-0.30	0.08
Technical Skill Dev. (TSD)	320	3.65	0.68	3.67	1.53	5.00	-0.34	0.15
– Practical Competency (PC)	320	3.71	0.72	3.80	1.40	5.00	-0.40	0.21
– Problem-Solving (PSA)	320	3.58	0.73	3.60	1.20	5.00	-0.28	-0.07
– Software Proficiency (SP)	320	3.67	0.70	3.60	1.60	5.00	-0.36	0.19
Self-Efficacy (SE)	320	3.74	0.66	3.75	1.63	5.00	-0.41	0.24

All skewness values within ± 1.0 and kurtosis within ± 2.0 , confirming approximate normality (Field, 2018).

4.3 Item-Level Analysis of Technical Skill Development

Table 6: Item-Level Means and Standard Deviations – Technical Skill Development Scale

Item Code	Item Description (Abbreviated)	Mean	SD	Rank
PC1	Can apply technical knowledge to practical problems	3.88	0.69	1

Item Code	Item Description (Abbreviated)	Mean	SD	Rank
PC2	Feel prepared to handle real-world technical challenges	3.74	0.72	3
PC3	Industry activities improved hands-on lab competencies	3.72	0.74	4
PC4	Can operate domain-specific equipment/tools confidently	3.65	0.76	8
PC5	Technical skills match industry entry-level requirements	3.55	0.80	12
PSA1	IAC improved analytical and problem-solving skills	3.76	0.71	2
PSA2	Can identify root causes in technical problems	3.61	0.74	9
PSA3	Can design solutions to open-ended engineering problems	3.44	0.81	15
PSA4	Debugging and troubleshooting ability has improved	3.58	0.76	11
PSA5	Can evaluate trade-offs in technical decision-making	3.52	0.79	13
SP1	Proficient in domain-specific software (MATLAB, Python, etc.)	3.72	0.70	5
SP2	Programming/coding proficiency improved via IAC	3.69	0.71	6
SP3	Can work with industry-standard software platforms	3.67	0.73	7
SP4	Comfortable using simulation/modelling tools	3.60	0.75	10
SP5	Can learn new software tools independently	3.47	0.80	14

Items ranked by mean score. PC = Practical Competency; PSA = Problem-Solving Ability; SP = Software Proficiency.

5. EXPLORATORY FACTOR ANALYSIS (EFA)

5.1 EFA Rationale and Method

Table 7: KMO and Bartlett's Test of Sphericity

Test	Statistic	Value	Interpretation
Kaiser-Meyer-Olkin (KMO)	Measure of Sampling Adequacy	0.882	Meritorious (> 0.80)
Bartlett's Test of Sphericity	Chi-Square (χ^2)	4,218.74	
	df	435	
	p-value	< 0.001	Matrix is factorable

KMO = 0.882 indicates excellent sampling adequacy; Bartlett's test confirms the correlation matrix is significantly different from an identity matrix ($p < 0.001$).

5.2 Factor Extraction and Variance Explained

Table 8: Factor Extraction – Eigenvalues and Variance Explained

Factor	Factor Label	Eigenvalue	% Variance	Cumulative %
F1	Internship Programs	5.84	19.47	19.47
F2	Live Projects	4.21	14.03	33.50
F3	Training & Workshops	3.18	10.60	44.10
F4	Industry Expert Interactions	2.74	9.13	53.23
F5	Curriculum Alignment	2.12	7.07	60.30
F6	Placement Relationships	1.20	4.00	64.30
Total	—	19.29	64.30%	—

Six-factor solution explaining 64.30% of total variance. Extracted using principal axis factoring with Promax rotation.

5.3 Pattern Matrix – Factor Loadings

Table 9: Pattern Matrix – Standardized Factor Loadings (Promax Rotation, N = 320)

Item	F1 (IP)	F2 (LP)	F3 (TW)	F4 (IEI)	F5 (CA)	F6 (PR)	h^2
IP1	0.81	0.08	0.06	0.09	0.05	0.07	0.68
IP2	0.78	0.11	0.04	0.12	0.08	0.06	0.64
IP3	0.76	0.09	0.08	0.07	0.11	0.09	0.62
IP4	0.74	0.07	0.12	0.10	0.06	0.08	0.60
LP1	0.10	0.79	0.07	0.08	0.05	0.06	0.65
LP2	0.09	0.77	0.09	0.11	0.07	0.08	0.62
LP3	0.07	0.75	0.10	0.09	0.09	0.07	0.59
TW1	0.06	0.08	0.80	0.09	0.07	0.05	0.66
TW2	0.09	0.10	0.77	0.08	0.10	0.06	0.63
TW3	0.08	0.07	0.74	0.11	0.08	0.09	0.58
IEI1	0.11	0.09	0.08	0.78	0.07	0.06	0.63
IEI2	0.10	0.08	0.09	0.76	0.09	0.08	0.60
CA1	0.07	0.06	0.09	0.10	0.77	0.08	0.61
CA2	0.09	0.08	0.07	0.08	0.74	0.09	0.57

Item	F1 (IP)	F2 (LP)	F3 (TW)	F4 (IEI)	F5 (CA)	F6 (PR)	h ²
PR1	0.08	0.07	0.06	0.09	0.08	0.79	0.64
PR2	0.09	0.09	0.08	0.07	0.10	0.76	0.60

Loadings ≥ 0.45 are considered significant (Hair et al., 2019). h^2 = communality. Only primary loadings shown for brevity; all cross-loadings < 0.30 .

6. CORRELATION ANALYSIS

6.1 Pearson Correlation Matrix

Table 10: Pearson Correlation Matrix – All Study Variables (N = 320)

Variable	IP	IEI	CA	LP	TW	PR	SE	TSD
IP	1.00							
IEI	0.54**	1.00						
CA	0.42**	0.48**	1.00					
LP	0.58**	0.51**	0.44**	1.00				
TW	0.49**	0.55**	0.38**	0.52**	1.00			
PR	0.46**	0.43**	0.40**	0.47**	0.45**	1.00		
SE	0.61**	0.54**	0.47**	0.60**	0.52**	0.43**	1.00	
TSD	0.68**	0.62**	0.51**	0.65**	0.60**	0.49**	0.66**	1.00

** $p < 0.01$ (2-tailed). IP=Internship Programs; IEI=Industry Expert Interactions; CA=Curriculum Alignment; LP=Live Projects; TW=Training & Workshops; PR=Placement Relationships; SE=Self-Efficacy; TSD=Technical Skill Development.

All IAC dimensions are significantly and positively correlated with Technical Skill Development ($p < 0.01$). IP shows the strongest bivariate correlation with TSD ($r = 0.68$), followed by LP ($r = 0.65$) and IEI ($r = 0.62$). Self-Efficacy is also significantly correlated with TSD ($r = 0.66$), supporting its inclusion as a mediator. Inter-dimension correlations among IAC variables are moderate ($r = 0.38$ – 0.58), indicating related but distinct constructs—supporting the six-factor structure.

6.2 Correlation with TSD Sub-Dimensions

Table 11: IAC Dimension Correlations with TSD Sub-Dimensions

IAC Dimension	Practical Competency (r)	Problem-Solving (r)	Software Proficiency (r)	TSD Overall (r)
Internship Programs	0.71**	0.62**	0.59**	0.68**
Industry Expert Interactions	0.58**	0.61**	0.57**	0.62**
Curriculum Alignment	0.49**	0.50**	0.46**	0.51**
Live Projects	0.63**	0.67**	0.58**	0.65**
Training & Workshops	0.55**	0.57**	0.62**	0.60**

IAC Dimension	Practical Competency (r)	Problem-Solving (r)	Software Proficiency (r)	TSD Overall (r)
Placement Relationships	0.46**	0.48**	0.44**	0.49**

**** p < 0.01 (2-tailed).** Notable: Live Projects shows the strongest correlation with Problem-Solving Ability ($r = 0.67$); Training & Workshops shows the strongest correlation with Software Proficiency ($r = 0.62$).

7. MULTIPLE AND HIERARCHICAL REGRESSION ANALYSIS

7.1 Regression Assumption Verification

Table 12: Regression Assumption Test Results

Assumption	Test Used	Statistic	Result / Decision
Normality of Residuals	Kolmogorov-Smirnov	$D = 0.041, p = 0.200$	Not violated
Homoscedasticity	Breusch-Pagan Test	$\chi^2 = 7.43, p = 0.282$	Not violated
Multicollinearity	VIF (all predictors)	VIF range: 1.38–2.14	Not violated (< 10)
Independence of Errors	Durbin-Watson	$d = 1.97$	Not violated (1.5–2.5)
Linearity	Ramsey RESET Test	$F = 1.42, p = 0.241$	Not violated
Influential Cases	Cook's Distance	Max $D = 0.08 (< 1.0)$	No influential outliers

All regression assumptions are satisfied. Analysis proceeds with confidence.

7.2 Standard Multiple Linear Regression

Table 13: Multiple Linear Regression – Predictors of Technical Skill Development ($N = 320$)

Predictor	B	SE(B)	β	t	p	95% CI (Lower)	95% CI (Upper)	VIF
(Constant)	0.482	0.194	—	2.485	0.013	0.100	0.864	—
Internship Programs	0.281	0.048	0.294	5.854	$< .001$	0.187	0.375	1.87
Live Projects	0.253	0.051	0.277	4.961	$< .001$	0.153	0.353	2.01
Industry Expert Interactions	0.214	0.052	0.241	4.115	$< .001$	0.112	0.316	1.94
Training & Workshops	0.198	0.050	0.222	3.960	$< .001$	0.100	0.296	1.78
Curriculum Alignment	0.163	0.046	0.189	3.543	$< .001$	0.073	0.253	1.52

Predictor	B	SE(B)	β	t	p	95% CI (Lower)	95% CI (Upper)	VIF
Placement Relationships	0.127	0.045	0.153	2.822	0.005	0.039	0.215	1.38

Dependent Variable: TSD Composite Score. $R = 0.781$; $R^2 = 0.610$; Adjusted $R^2 = 0.603$; $F(6, 313) = 81.74$; $p < 0.001$; Std. Error of Estimate = 0.429.

The regression model accounts for 61.0% of variance in Technical Skill Development (Adjusted $R^2 = 0.603$). All six predictors are significant. Internship Programs ($\beta = 0.294$) and Live Projects ($\beta = 0.277$) are the strongest unique contributors. The 95% confidence intervals for all beta coefficients exclude zero, confirming robustness. The narrow CI widths (≤ 0.188) indicate precise parameter estimates.

7.3 Hierarchical Regression Analysis

Hierarchical regression was conducted in three blocks to assess incremental explanatory power: Block 1 (demographic controls: gender, institution type, programme level, year of study), Block 2 (IAC dimensions), Block 3 (Self-Efficacy).

Table 14: Hierarchical Regression – Model Comparison

Block	Variables Entered	R^2	ΔR^2	ΔF	p (ΔF)
Block 1	Demographic controls (4 variables)	0.112	0.112	9.84	< .001
Block 2	IAC dimensions (6 variables)	0.610	0.498	66.37	< .001
Block 3	Self-Efficacy (1 variable)	0.648	0.038	33.12	< .001

ΔR^2 = Change in R^2 ; ΔF = F-change statistic. All increments statistically significant at $p < .001$.

Demographics alone explain 11.2% of TSD variance. The addition of IAC dimensions (Block 2) produces a substantial ΔR^2 of 0.498 (F -change = 66.37, $p < .001$), confirming that IAC dimensions explain the majority of the predictable variance. Self-efficacy adds a further 3.8% ($\Delta R^2 = 0.038$, F -change = 33.12, $p < .001$), highlighting its independent contribution beyond IAC activities. The total model explains 64.8% of TSD variance.

7.4 Sub-Dimension Regression Results

Table 15: Regression of IAC Dimensions on TSD Sub-Dimensions

Predictor	$\beta \rightarrow$ Practical Competency	$\beta \rightarrow$ Problem-Solving	$\beta \rightarrow$ Software Proficiency
Internship Programs	0.321***	0.264***	0.248***
Live Projects	0.271***	0.310***	0.231***
Industry Expert Interactions	0.221***	0.248***	0.218***
Training & Workshops	0.187***	0.203***	0.271***
Curriculum Alignment	0.176***	0.192***	0.168***
Placement Relationships	0.141**	0.148**	0.138**

Predictor	$\beta \rightarrow$ Practical Competency	$\beta \rightarrow$ Problem-Solving	$\beta \rightarrow$ Software Proficiency
R ²	0.574	0.596	0.558
F	69.72***	75.98***	65.10***

*** $p < .001$; ** $p < .01$. Standardized beta coefficients shown. Most notable: Live Projects is the strongest predictor of Problem-Solving Ability ($\beta = 0.310$); Training & Workshops is the strongest predictor of Software Proficiency ($\beta = 0.271$).

8. GROUP COMPARISON ANALYSES: ANOVA AND T-TESTS

8.1 One-Way ANOVA: Technical Skill Development by Institution Type

H₆ postulates significant differences in TSD across institution types. One-way ANOVA was conducted with three groups: Autonomous Colleges ($n = 132$), Affiliated Colleges ($n = 110$), and Deemed Universities ($n = 78$). Levene's test confirmed homogeneity of variances ($F = 1.82$, $p = 0.164$).

Table 16: One-Way ANOVA – TSD by Institution Type

Source	Sum of Squares	df	Mean Square	F	p	η^2
Between Groups	12.847	2	6.424	14.82	< .001	0.086
Within Groups	135.641	317	0.428			
Total	148.488	319				

$\eta^2 = 0.086$ indicates a medium effect size (Cohen, 1988: small = 0.01, medium = 0.06, large = 0.14).

The ANOVA is statistically significant ($F(2, 317) = 14.82$, $p < .001$), confirming H₆. The effect size ($\eta^2 = 0.086$) is medium, indicating that institution type explains approximately 8.6% of variance in TSD. Post-hoc Tukey HSD tests were conducted to identify pairwise differences:

Table 17: Tukey HSD Post-Hoc Tests – TSD by Institution Type

Comparison	Mean Difference (I – J)	SE	p (Tukey)	95% CI	Interpretation
Autonomous vs. Affiliated	0.29	0.083	< .001	[0.10, 0.48]	Significant
Autonomous vs. Deemed Univ.	0.38	0.094	< .001	[0.16, 0.60]	Significant
Affiliated vs. Deemed Univ.	0.09	0.097	0.617	[-0.14, 0.32]	Not Significant

Autonomous Colleges show significantly higher TSD than both Affiliated Colleges and Deemed Universities. Affiliated Colleges and Deemed Universities do not differ significantly from each other.

Table 18: Group Means – TSD and IAC by Institution Type

Measure	Autonomous Colleges (M ± SD)	Affiliated Colleges (M ± SD)	Deemed Universities (M ± SD)
TSD Overall	3.84 ± 0.61	3.55 ± 0.66	3.46 ± 0.72
Practical Competency	3.92 ± 0.65	3.60 ± 0.71	3.54 ± 0.76
Problem-Solving Ability	3.76 ± 0.67	3.47 ± 0.72	3.38 ± 0.75
Software Proficiency	3.83 ± 0.63	3.58 ± 0.68	3.48 ± 0.73
IAC Composite	3.84 ± 0.56	3.48 ± 0.64	3.41 ± 0.67

Autonomous Colleges consistently outperform other institution types across all TSD sub-dimensions and IAC composite.

8.2 One-Way ANOVA: TSD by Year of Study

Table 19: One-Way ANOVA – TSD by Year of Study

Source	Sum of Squares	df	Mean Square	F	p	η^2
Between Groups	8.912	3	2.971	6.72	< .001	0.060
Within Groups	139.576	316	0.442			
Total	148.488	319				

$F(3, 316) = 6.72, p < .001, \eta^2 = 0.060$ (medium effect). TSD increases with year of study.

Table 20: Group Means – TSD by Year of Study

Year of Study	N	Mean TSD	SD	Post-Hoc Grouping
1st Year	64	3.38	0.66	Group A
2nd Year	106	3.58	0.65	Group A/B
3rd Year	101	3.74	0.67	Group B
4th / Final Year	49	3.91	0.61	Group C

Tukey HSD: 1st year differs significantly from 3rd ($p = .004$) and 4th year ($p < .001$). 4th year significantly higher than all others ($p < .01$).

8.3 Independent Samples t-Test: TSD by Programme Level (UG vs. PG)

H_7 predicts significant differences in TSD between UG and PG students. Levene's test confirmed equal variances ($F = 1.44, p = 0.231$).

Table 21: Independent Samples t-Test – TSD by Programme Level

Measure	UG (n=232) M ± SD	PG (n=88) M ± SD	t(318)	p	Cohen's d	Interpretation
TSD Overall	3.54 ± 0.66	3.96 ± 0.62	6.44	< .001	0.65	Medium-Large
Practical Competency	3.60 ± 0.70	4.03 ± 0.64	6.27	< .001	0.64	Medium-Large

Measure	UG (n=232) M ± SD	PG (n=88) M ± SD	t(318)	p	Cohen's d	Interpretation
Problem-Solving Ability	3.46 ± 0.70	3.88 ± 0.66	5.98	< .001	0.62	Medium-Large
Software Proficiency	3.57 ± 0.68	3.96 ± 0.64	5.74	< .001	0.59	Medium
IAC Composite	3.55 ± 0.60	3.82 ± 0.63	4.28	< .001	0.44	Small-Medium

Cohen's d: small = 0.20, medium = 0.50, large = 0.80 (Cohen, 1988). PG students demonstrate significantly higher TSD across all sub-dimensions.

8.4 Independent Samples t-Test: TSD by Gender

Table 22: Independent Samples t-Test – TSD and IAC by Gender

Measure	Male (n=166) M ± SD	Female (n=152) M ± SD	t(316)	p	Cohen's d
TSD Overall	3.70 ± 0.66	3.59 ± 0.70	1.52	0.130	0.16
Practical Competency	3.74 ± 0.70	3.67 ± 0.74	0.92	0.358	0.10
Problem-Solving Ability	3.62 ± 0.71	3.54 ± 0.75	1.05	0.295	0.11
Software Proficiency	3.78 ± 0.67	3.51 ± 0.71	3.74	< .001	0.39
IAC Composite	3.67 ± 0.61	3.58 ± 0.63	1.37	0.172	0.14

Significant gender difference exists only for Software Proficiency ($t = 3.74$, $p < .001$, $d = 0.39$). Overall TSD and other sub-dimensions do not differ significantly by gender.

The findings are complex; there is no significant gender gap in all TSD items, but a statistically significant and practically significant gap is found in Software Proficiency ($d = 0.39$). It is a targeted finding and more of a skills gap than a lack of industry engagements with software.

9. CHI-SQUARE TESTS OF INDEPENDENCE

9.1 Rationale

Chi-square tests of independence were performed to explore the relationships between categorical demographic variables and categorical IAC participation levels. To this end, IAC composite scores were divided into three groups: Low IAC (< 2.67), Moderate IAC ($2.67-3.67$) and High IAC (> 3.67). Technical Skill Development was also separated. This allows us to explore the differences in patterns of engagement with IAC by demographic group.

Table 23: Chi-Square Test Results – Demographic Variables and IAC Participation Level

Association Tested	N	χ^2	df	p	Cramér's V	Interpretation
Gender × IAC Level	318	4.82	2	0.090	0.123	Not Significant

Association Tested	N	χ^2	df	p	Cramér's V	Interpretation
Programme Level $\times$ IAC Level	320	18.74	2	< .001	0.242	Significant (Medium)
Institution Type $\times$ IAC Level	320	31.48	4	< .001	0.222	Significant (Medium)
Year of Study $\times$ IAC Level	320	22.16	6	0.001	0.186	Significant (Small-Medium)
Stream $\times$ IAC Level	320	14.62	4	0.006	0.151	Significant (Small)
Gender $\times$ TSD Level	318	5.14	2	0.077	0.127	Not Significant
Programme Level $\times$ TSD Level	320	21.38	2	< .001	0.258	Significant (Medium)
Institution Type $\times$ TSD Level	320	28.92	4	< .001	0.213	Significant (Medium)

Cramér's V: small = 0.10, medium = 0.30, large = 0.50. Programme level and institution type show the strongest associations with both IAC participation and TSD level.

Table 24: Cross-Tabulation – Programme Level $\times$ IAC Participation Level

IAC Level	UG (n=232)	UG (%)	PG (n=88)	PG (%)	Total
Low IAC (< 2.67)	62	26.7%	8	9.1%	70
Moderate IAC (2.67–3.67)	118	50.9%	38	43.2%	156
High IAC (> 3.67)	52	22.4%	42	47.7%	94
Total	232	100%	88	100%	320

$\chi^2 (2) = 18.74, p < .001, \text{Cramér's } V = 0.242.$ PG students are substantially more likely to report High IAC engagement (47.7%) compared to UG students (22.4%).

10. MEDIATION ANALYSIS: SELF-EFFICACY AS MEDIATOR

10.1 Theoretical Basis

According to Social Cognitive Theory (Bandura, 1986), the IAC activities can improve the process of technical skills development directly and indirectly by increasing students' self-efficacy, which is their confidence in being able to perform technical tasks. The purpose of this study is to examine the possibility of a mediation effect between IAC and TSD with the Baron and Kenny (1986) causal steps approach followed by Sobel (1982) test for the significance of the mediation effect. The independent variable (IV) is the IAC composite score; the dependent variable (DV) is the TSD; the proposed mediator (M) is self-efficacy.

10.2 Baron and Kenny Mediation Steps

Table 25: Mediation Analysis Steps – Self-Efficacy Mediating IAC → TSD

Step	Path	β	SE	t	p	Condition Met?
Step 1	IAC → TSD (c: total effect)	0.853	0.066	12.92	< .001	Yes (IV → DV significant)
Step 2	IAC → Self-Efficacy (a: IV → Mediator)	0.741	0.059	12.56	< .001	Yes (IV → M significant)
Step 3a	Self-Efficacy → TSD (b: M → DV, controlling IV)	0.312	0.058	5.38	< .001	Yes (M → DV significant)
Step 3b	IAC → TSD (c': direct effect, controlling M)	0.622	0.071	8.76	< .001	Partial Mediation

All four Baron & Kenny steps are satisfied. Reduction in β from $c = 0.853$ to $c' = 0.622$ confirms partial mediation by self-efficacy.

10.3 Sobel Test and Indirect Effect

Table 26: Sobel Test – Significance of Indirect Effect

Parameter	Value
a (IAC → Self-Efficacy)	0.741
b (Self-Efficacy → TSD IAC)	0.312
SE(a)	0.059
SE(b)	0.058
Indirect Effect ($a \times b$)	0.231
Standard Error of Indirect Effect	0.054
Sobel z-statistic	4.21
p-value (two-tailed)	< .001
95% CI of Indirect Effect	[0.131, 0.331]
Proportion Mediated ($a \times b / c$)	27.1%

The indirect effect ($a \times b = 0.231$) is statistically significant (Sobel $z = 4.21$, $p < .001$), with the 95% CI excluding zero. Self-efficacy mediates 27.1% of the total IAC effect on TSD.

The mediation analysis results support H_8 : the relationship between IAC and TSD is significant and partial mediation (mediation effect is significant but not fully mediated). The direct path is still important, $c' = 0.622$, $p < .001$, which means there is partial (not complete) mediation. IAC's had both direct effects on technical skills ($c' = 0.622$) and indirect effects on technical skills by improving self-efficacy beliefs, which in turn led to additional technical skill development (indirect effect = 0.231, 27.1% of

total effect). This finding has implications for practice: the provision of IAC activities should go hand-in-hand and go beyond that to explicitly promote self-efficacy through goal-setting, reflective journals and peer learning.

11. STUDENT SEGMENTATION: K-MEANS CLUSTER ANALYSIS.

11.1 Rationale and Method

The students were segmented into homogeneous groups using k-means cluster analysis on their exposure to IAC and TSD outcome. When student groups are segmented, targeted interventions are possible instead of a “one size fits all” approach. Variables used were the 6 dimension scores from the IAC (plus three sub-dimension scores from the TSD – a total of 9) which had been 'standardised' (z-scores) before clustering. The elbow method on WSS and silhouette coefficient were used to determine the optimal number of clusters..

Table 27: Cluster Solution Evaluation – Within-Cluster Sum of Squares and Silhouette

Number of Clusters (k)	Within-Cluster SS	Silhouette Coefficient	Recommendation
2	1,842.4	0.312	
3	1,218.6	0.387	Optimal (elbow + silhouette peak)
4	1,086.3	0.361	
5	978.4	0.339	

k = 3 is the optimal solution based on elbow criterion and peak silhouette coefficient (0.387). Three distinct student segments are identified.

11.2 Cluster Profiles

Table 28: K-Means Cluster Analysis – Cluster Profiles (Means, N = 320)

Variable	Cluster 1: High Engagement (n=98, 30.6%)	Cluster 2: Moderate Engagement (n=148, 46.3%)	Cluster 3: Low Engagement (n=74, 23.1%)
Internship Programs	4.42	3.72	2.71
Industry Expert Interactions	4.28	3.61	2.68
Curriculum Alignment	4.01	3.37	2.57
Live Projects	4.31	3.54	2.60
Training & Workshops	4.38	3.67	2.74
Placement Relationships	4.11	3.50	2.58
IAC Composite	4.25	3.57	2.65
Practical Competency	4.28	3.68	2.84

Variable	Cluster 1: High Engagement (n=98, 30.6%)	Cluster 2: Moderate Engagement (n=148, 46.3%)	Cluster 3: Low Engagement (n=74, 23.1%)
Problem-Solving Ability	4.14	3.54	2.78
Software Proficiency	4.21	3.62	2.81
TSD Overall	4.21	3.61	2.81
Self-Efficacy	4.34	3.70	2.82

All cluster differences are statistically significant (ANOVA $p < .001$ for all variables). Means represent original Likert scale scores (1–5).

Table 29: Cluster Demographic Composition

Demographic	Cluster 1 High (n=98)	Cluster 2 Moderate (n=148)	Cluster 3 Low (n=74)
PG Students (%)	52.0%	26.4%	8.1%
Autonomous College (%)	54.1%	42.6%	20.3%
Engineering Stream (%)	48.0%	54.1%	60.8%
Final Year (%)	30.6%	14.2%	4.1%
Male (%)	54.1%	52.0%	50.0%

Cluster 1 (High Engagement) is disproportionately composed of PG students, autonomous college students, and final-year students — reflecting accumulation of IAC opportunities with academic seniority.

Three analytically different groups of students emerge. Students belonging to Cluster 1 (High Engagement – 30.6%) are those who have consistently high exposure to IAC and TSD; are PG students and are from autonomous colleges. The largest group are in Cluster 2, 'Moderate Engagement' (46.3%) – these are the students having the 'average' experience in the region. Students in Cluster 3 (Low Engagement, 23.1%) have low exposure to IAC and have the lowest TSD scores, and are significantly under-represented in affiliated colleges for the early years of study. A segmentation also suggests that there is ample opportunity for early year intervention programmes, tailored to cluster 3 students, within affiliated colleges to move these students into cluster 2 or cluster 1 students.

12. STRUCTURAL EQUATION MODELLING (SEM) – PATH ANALYSIS

12.1 SEM Model Specification

A structural equation model was set up to test simultaneously the measurement model (CFA) and the structural paths between latent constructs. The construction exogenous to the model is IAC Engagement, which includes all of the six dimensions of the IAC; Self-Efficacy is the mediating latent construct, and Technical Skill Development (three indicators: Practical Competency, Problem-Solving Ability, Software Proficiency) is the endogenous construct. We have used the Maximum Likelihood estimation for AMOS 26.

12.2 SEM Model Fit

Table 30: SEM Model Fit Indices

Fit Index	Full Model Value	Threshold	Interpretation
χ^2/df	1.487	< 3.0	Excellent
CFI	0.938	> 0.90	Good
TLI	0.930	> 0.90	Good
RMSEA	0.055	< 0.08	Acceptable
SRMR	0.051	< 0.08	Good
AIC (vs. Saturated)	1,824.3 vs. 2,016.8	Lower is better	Model preferred

The SEM model demonstrates good fit, supporting the proposed theoretical structure.

12.3 Standardized Path Coefficients

Table 31: SEM Standardized Path Coefficients

Path	Standardized β	SE	Critical Ratio (t)	p	Hypothesis
IAC Engagement → Self-Efficacy	0.724	0.062	11.68	< .001	Supported
IAC Engagement → TSD (Direct)	0.591	0.071	8.32	< .001	Supported
Self-Efficacy → TSD	0.298	0.059	5.05	< .001	Supported (Partial Mediation)
IAC Engagement → TSD (Total)	0.807	—	—	< .001	Supported
Indirect Effect (via SE)	0.216	0.051	4.24	< .001	Significant
Internship Programs → IAC Engagement	0.812	0.058	13.99	< .001	Confirmed
Live Projects → IAC Engagement	0.784	0.061	12.85	< .001	Confirmed
Training & Workshops → IAC Engagement	0.741	0.063	11.76	< .001	Confirmed
Industry Expert Int. → IAC Engagement	0.718	0.065	11.05	< .001	Confirmed
Curriculum Alignment → IAC Engagement	0.681	0.067	10.16	< .001	Confirmed

Path	Standardized β	SE	Critical Ratio (t)	p	Hypothesis
Placement Relationships → IAC Engagement	0.624	0.072	8.67	< .001	Confirmed

All paths are statistically significant ($p < .001$). Internship Programs shows the strongest loading on the IAC second-order factor ($\beta = 0.812$).

The SEM results confirm the overall structural model. The total effect of IAC Engagement on TSD ($\beta = 0.807$) decomposes into a substantial direct effect ($\beta = 0.591$) and a significant indirect effect via Self-Efficacy ($\beta = 0.216$). Internship Programs ($\beta = 0.812$) and Live Projects ($\beta = 0.784$) show the highest loadings on the second-order IAC factor, corroborating the regression findings. The model provides a comprehensive structural account of how IAC translates into technical skill development.

13. DISCUSSION OF FINDINGS

13.1 Overall IAC–Skill Development Relationship:

This result of a positive strong correlation between IAC Engagement and Technical Skill Development ($r = 0.74$, SEM total effect $\beta = 0.807$) further validates and extends previous studies. This regression model that accounts for 61% of the variance in TSD (64.8% with self-efficacy) is one of the highest reported in the regional literature of Indian HEI. This is significant for immediate and direct policy implications: it indicates that IAC is not simply an institutional 'add-on', but a key element of the competency development process.

13.2 Differential Effects Across IAC Dimensions

The disaggregated regression analysis shows important differential effects that cannot be seen in the aggregate level. As is expected from Kolb's (1984) experiential learning cycle, Internship Programs and Live Projects are the two most predictive qualities, aligning with the nodes of the cycle that are the most generative of deep learning: concrete experience and active experimentation. Training & Workshops exhibits particularly strong predictive ability for Software Proficiency ($\beta = 0.271$), consistent with the nature of the training and its intensity, which focuses on software. The finding from the sub-dimension regression, that Live Projects is the strongest predictor of Problem-Solving Ability ($\beta = 0.310$), is consistent with the literature on problem-based learning (Blumenfeld et al., 1991) which shows that ill-structured, open-ended industrial problems require integrative reasoning that classroom exercises cannot duplicate.

13.3 Disparity (IPD) – Institutional and Programme-Level

The significance of the difference in the TSD between the Autonomous Colleges and the Affiliated Colleges and Deemed Universities ($\eta^2 = 0.086$) highlights structural advantages: autonomous colleges have more freedoms in their curriculum that allows the incorporation of IAC activities, can negotiate MoUs on their own, and generally have a better network with the industries. The lack of significance difference between Affiliated Colleges and Deemed Universities implies that rather than the university/college difference, autonomy is the most important structural moderator. The significant differences between the performances of PG and UG students (Cohen's $d = 0.65$) in the t-test is attributed to the greater academic maturity and exposure to IAC by PG students as evidenced by the chi-square analysis. Longitudinal validity for the cross sectional finding is provided by the ANOVA result that the TSD increased with year of study.

13.4 The Self-Efficacy Mediation Mechanism

The partial mediation finding (Sobel $z = 4.21$, proportion mediated = 27.1%) helps the development of theory by providing an explanation for one pathway by which IAC 'works'. IAC activities, especially internships and live projects, help build students' confidence in their technical skills and ability. This newfound sense of self-efficacy in turn leads to more involvement with complex technical activities, which further enhances the learning process. Practical implication: Integrating IAC activities and providing structured reflection elements (portfolio development, self-assessment rubrics, mentor feedback sessions) will lead to more self-efficacy and, as a consequence, to greater downstream skills.

13.5 Student Segmentation Implications

The three-cluster solution indicates that a small proportion (23.1%) of students (Cluster 3: Low Engagement) have systematically low IAC exposure and low TSD outcomes. This group is focused on affiliated colleges and early study years. These students are the highest priority intervention target: a 0.80 unit increase (from $M = 2.81$ to $M = 3.61$) would correspond to the difference between 'below average' and 'above average' in technical competency as predicted by the IAC. The 46.3% in Cluster 2 are the 'middle majority' in which there is scope for targeted improvements to bring about population level skills gains most effectively.

14. RECOMMENDATIONS AND POLICY IMPLICATIONS.

14.1 For Higher Education Institutions

Focus attention on structural improvement to Internship Programs and Live Project opportunities, the two most important TSD predictors. HEIs should establish internship quality criteria (at least 8 weeks, learning objectives, responsibility of the industrial supervisor, evaluation rubric). The MoU negotiation, program monitoring and standardized outcome data collection should be done through a centralized IAC Management Cell. MoUs should be facilitated at direct industry level with colleges affiliated to APSCHE to achieve specific goals rather than at university level.

In order to address the self-efficacy mediation mechanism, structured reflection components need to be included with all IAC activities, namely internship portfolios, reflective journals, peer feedback sessions, and structured mentor debriefs. Low cost additions can greatly magnify the skill development gains of IAC activities that are already in place.

14.2 For APSCHE and State Policymakers

The substantial difference between the institutions of various types ($\eta^2 = 0.086$) necessitates action by the policy makers – APSCHE should provide a mechanism to operationalise the concept of IAC design in high-performing affiliated colleges beyond the process of compliance and instead enable genuine curricular freedom. The NEP 2020 internship requirement of 40 credits should be achieved based on quality and not compliance through attendance. APSCHE can publish an annual Regional IAC Quality Index, which will put the institutions on a level playing field and provide accountability.

Although the gender gap in Software Proficiency ($d = 0.39$, $p < .001$) is not statistically significant when considering TSD overall, it does justify gender specific interventions, such as introducing gender-inclusive programmes in Software Proficiency, providing coding bootcamps for female students supported by industry, and implementing gender-disaggregated IAC reporting.

14.3 For Industry Partners

The Visakhapatnam chapter of CII/NASSCOM should co-create a Regional Industry-Academic Interface Council to create a uniform and scale-up the structured IAC activities among the member companies. Industry partners develop different engagement tracks that match the three student clusters identified: Foundation Awareness tracks for Cluster 3 students (particularly in affiliated colleges); Applied project tracks for Cluster 2 students; Advanced research / innovation tracks for Cluster 1 students. A segmented approach ensures that maximum investment efficiency is used in the industry.

14.4 Priority Action Matrix

Table 32: Priority Action Matrix for IAC Strengthening

Priority	Action	Responsible Party	Target Segment	Expected Impact
1 – Critical	Formalize internship quality standards & assessment rubrics	HEIs + APSCHE	Cluster 3 students (Affiliated, UG, 1st–2nd year)	High ($\beta = 0.294$)
2 – Critical	Establish Live Project Centres in all autonomous colleges	HEIs + CII	Cluster 1 & 2	High ($\beta = 0.277$)

Priority	Action	Responsible Party	Target Segment	Expected Impact
3 – High	Industry Advisory Board mandate for all HEIs (> 500 students)	APSCHE	All institutions	Medium-High
4 – High	Gender-inclusive software bootcamps via industry partnership	Industry + HEIs	Female students	Targeted ($d = 0.39$)
5 – High	Reflection-augmented internship portfolios	HEIs	All students	SE mediation 27%
6 – Medium	Curriculum review with industry voting members (bi-annual)	HEIs + Industry	All students	Medium ($\beta = 0.189$)
7 – Medium	Regional IAC Quality Index (annual publication)	APSCHE	Policy/institutional	Accountability
8 – Medium	Autonomy pathway for high-performing affiliated colleges	APSCHE	Affiliated colleges	Structural reform

Actions prioritized by effect size, statistical significance, and feasibility within Visakhapatnam regional context.

15. CONCLUSION, LIMITATIONS, AND FUTURE RESEARCH

15.1 Conclusion

This study is the most analytical and comprehensive regional empirical analysis of industry-academy collaboration and technical skill development till date in higher education of Andhra Pradesh region. Evidence across the multi-method analytical framework used (descriptive analysis, correlation, EFA, CFA, multiple and hierarchical regression, ANOVA, t-tests, chi-square tests, mediation analysis, cluster segmentation, SEM) indicates that IAC engagement is a statistically significant, practically important, and multi-mechanistic predictor of student technical skill development.

The main findings of the study are: (1) quantification of the relative predictive power of six IAC dimensions, which can be used to prioritize policies; (2) identification of institutional-type and programme-level disparities that call for structural reform; (3) mediation evidence that confirmed the role of self-efficacy as a 27.1% mediator between IAC and the TSD relationship; (4) cluster-based student segmentation, which identified the low-engagement sub-population of 23.1% to be targeted for intervention; and (5) SEM validation of the proposed theoretical model.

15.2 Limitations

There are a number of caveats to its use. First, cross sectional design does not allow for definitive causal inferences as would longitudinal studies. Second, self-report measures may be influenced by social desirability and response set effects which are mitigated if administered anonymously. Third, the sample is limited to the district of Visakhapatnam and findings may not be applicable to other districts and/or settings across India. Fourth, it was not possible to gather employer ratings of the graduates' technical skills as an external validation measure. Fifth, prior academic achievement (CGPA) was not controlled for which is a potential confound.

15.3 Future Research Directions

Future studies should: (1) Use longitudinal panel designs to follow cohorts from first year into their employment to validate the IAC-skill-employability pathway; (2) Incorporate an external criterion variable in terms of employer assessment of technical competency; (3) Expand geographies by comparing performance in IACs from the regions of Visakhapatnam, Vijayawada, Guntur and Tirupati in Andhra Pradesh; (4) Identify the moderating role of industry partner characteristics (firm size, sector, depth of involvement) of IAC effectiveness; (5) Explore digital IAC formats that were developed since the onset of COVID-

19 (e.g. virtual internships, online live projects); and (6) Incorporate experimental or quasi-experimental designs to infer causal relationships in specific IAC interventions..

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- [30] Appendix: Hypothesis Testing Summary

Table 33: Complete Hypothesis Testing Summary

Hypothesis	Test Used	Key Statistic	p	Effect Size	Decision
H ₁ : IP → TSD	Regression (β)	β = 0.294	< .001	—	Supported
H ₂ : IEI → TSD	Regression (β)	β = 0.241	< .001	—	Supported
H ₃ : CA → TSD	Regression (β)	β = 0.189	< .001	—	Supported
H _{4a} : LP → TSD	Regression (β)	β = 0.277	< .001	—	Supported
H _{4b} : TW → TSD	Regression (β)	β = 0.222	< .001	—	Supported
H ₅ : PR → TSD	Regression (β)	β = 0.153	.005	—	Supported
H ₆ : TSD diff. by Institution Type	One-Way ANOVA	F(2,317) = 14.82	< .001	η ² = 0.086	Supported
H ₇ : TSD diff. by Programme Level	Independent t-test	t(318) = 6.44	< .001	d = 0.65	Supported
H ₈ : SE mediates IAC → TSD	Sobel Test	z = 4.21	< .001	27.1% mediated	Supported

All 9 hypotheses supported at the 5% significance level. Statistical methods: SPSS 26 & AMOS 26.