



## Dual-Track Career Preparation: Integrating Digital Skill Acquisition with Traditional Undergraduate Curricula

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### ABSTRACT

Undergraduate education in India has expanded into the world's second-largest higher education system while employers continue to report that discipline-based degrees alone no longer signal work-readiness in digitally intensive labour markets. Curricula remain predominantly single-track: disciplinary content is delivered with rigour, whereas digital capability is displaced into optional, unassessed, co-curricular space. The consequences of this architectural choice, and the extent to which institutional type conditions it, remain empirically unresolved. This study tests whether digital skill acquisition and traditional disciplinary depth operate as complementary rather than competing tracks in producing perceived employability and career readiness, whether curricular integration outperforms co-curricular delivery, and whether institutional type and digital self-efficacy moderate these relationships. Stratified random sampling generated 3,085 valid responses (63.2% effective response rate) from undergraduates across all disciplinary streams in 1,427 university-level institutions: central universities (n = 682), state public and private universities (n = 1,688), deemed-to-be universities (n = 458) and Institutes of National Importance (n = 257). Validated five-point Likert instruments were

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analysed in SPSS 29 and PROCESS v4.2 through exploratory and confirmatory factor analysis, Harman's single-factor test, one-way MANOVA, hierarchical regression, propensity score matching with independent-samples t-tests, moderation analysis and structural equation modelling. Dual-track preparation is an architectural rather than a volumetric problem: credit-bearing embedding, self-efficacy scaffolding and institution-sensitive regulatory design outperform bolt-on skilling.

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## 1. Introduction

The relationship between undergraduate education and labour market entry has been renegotiated twice in a generation. The first renegotiation was volumetric: participation expanded, degrees proliferated, and the signalling value of a first degree diluted as it became common rather than distinctive (Tholen, 2016; Noui, 2020). The second renegotiation is compositional, and it is still in progress. Work itself has been re-specified around data handling, platform fluency, automation-adjacent judgement and digital collaboration, such that the marginal graduate is now assessed less on what discipline they studied than on what they can operationally do within digitised workflows (Alekseeva et al., 2021; Hoe, 2024). Universities have responded to the second renegotiation using instruments designed for the first. Digital capability has been appended to the undergraduate experience through optional certificate programmes, vacation bootcamps, placement-cell workshops and club activity, while the credit-bearing, examined, faculty-owned core of the degree has largely retained its pre-digital shape (Kornelakis & Petrakaki, 2020; Daubney, 2021).

India presents the most consequential setting in which to examine this mismatch. The system enrolls upwards of forty million students across a deliberately differentiated institutional architecture, comprising central universities, state public and private universities, deemed-to-be universities and Institutes of National Importance, each with distinct funding regimes, autonomy envelopes, faculty markets and industry proximity. Persistent employability deficits among Indian graduates have been documented for over a decade and have been attributed less to aggregate underinvestment than to the structural disconnection between curricular content and occupational demand (Unni, 2016; Agrawal, 2012; Khare, 2021). The National Education Policy 2020 responded with a vocabulary of multidisciplinary, credit flexibility and vocational integration, but policy vocabulary does not by itself determine whether a digital competency is a graded course outcome or a voluntary weekend activity. That determination is made institution by institution, and its effects are the empirical subject of this paper.



Three gaps motivate the study. First, the dominant framing in employability research treats digital skills and disciplinary knowledge as substitutes competing for finite curricular time, whereas human capital reasoning predicts complementarity between general-purpose and specific capability stocks (Becker, 1962; Marginson, 2017). The complementarity claim has rarely been tested with adequate statistical power across institutional strata. Second, the literature on embedding employability is rich in case description but thin in counterfactual identification: comparisons of curricular-integrated and co-curricular delivery are typically confounded by selection, because motivated students self-select into optional skilling (Valero et al., 2020; Gill, 2018). Third, institutional moderation is undertheorised. Studies routinely control for institution type as a nuisance variable rather than modelling it as a conditioning structure that changes the return on student effort (Strayhorn & DeVita, 2009; Croucher & Woelert, 2015). Where students accumulate identical digital capability but convert it into employability at different rates, the explanatory object is the institution, not the student.

This paper therefore models dual-track career preparation as a designed architecture with measurable returns. It estimates the direct contribution of digital skill acquisition alongside traditional disciplinary depth, isolates the delivery-mode effect using propensity score matching, and specifies institutional type and digital self-efficacy as moderators of conversion efficiency. The contribution is threefold: a theoretically grounded complementarity model of dual-track preparation, a selection-corrected estimate of the curricular embedding premium, and evidence that identical skill inputs yield unequal employability returns across a stratified national system.

## **2. Theoretical Framework and Review of Literature**

### **2.1 Human Capital Theory and the Complementarity of Capability Stocks**

Human capital theory specifies education as investment in productive capacity, distinguishing general capital that transfers across employers from specific capital tied to particular tasks or firms (Becker, 1962). Applied to undergraduate design, disciplinary depth constitutes durable general capital, conferring analytical structure and credentialled legitimacy, while digital skill constitutes a rapidly depreciating but highly transferable capital form whose returns are realised at the point of labour market entry (Gorlitz & Tamm, 2016). The theoretical prediction is complementarity rather than substitution: digital tools amplify the productive expression of disciplinary reasoning, and disciplinary reasoning supplies the problem framing without which tool fluency is mechanical. Critiques of the theory's economism are well taken, particularly its inattention to positional competition and institutional gatekeeping (Marginson, 2017; Tholen, 2016), and this study incorporates that critique by modelling institutional structure as a moderator rather

than a control. The complementarity prediction, however, remains analytically productive and directly testable, since it implies that digital skill should retain incremental predictive power over employability after disciplinary depth and socio-demographic endowments are partialled out.

Employability research has progressively widened the capital metaphor. Graduate capital models specify human, social, cultural, identity and psychological capitals as jointly necessary (Tomlinson, 2017; Clarke, 2017), and the Employability Capital Growth Model synthesises two decades of evidence into a multi-capital growth architecture (Donald et al., 2023). Psychological capital operates partly through skill perception (Ayala Calvo & Manzano Garcia, 2020), while capital conversion is mediated by agency and context rather than automatic (Pham et al., 2019). This body of work establishes that possession and conversion are distinct problems, a distinction this study operationalises by separating skill acquisition from the institutional conditions governing its conversion into perceived employability.

## 2.2 Experiential Learning Theory and the Architecture of Curricular Delivery

Experiential learning theory holds that capability forms through a recursive cycle of concrete experience, reflective observation, abstract conceptualisation and active experimentation, and that learning spaces either support or truncate that cycle (Kolb & Kolb, 2005; Kolb & Kolb, 2022). The theory carries an underappreciated implication for curricular design. Co-curricular skilling typically delivers concrete experience and active experimentation while systematically omitting assessed reflection and conceptual consolidation, because no examiner requires them. Curricular integration, by contrast, enforces the full cycle through graded assessment, faculty feedback and disciplinary anchoring. Delivery mode is therefore not a logistical detail but a determinant of cycle completeness, and should produce differential outcomes even at equal exposure hours.

Empirical work is consistent with this reading. Work-integrated learning shows robust associations with employability outcomes when embedded and supervised (Oliver, 2015; Mabungela & Mtiki, 2024), capstone courses shift employability perceptions measurably (Gilbert & Wingrove, 2019), and interactive oral assessment develops graduate attributes that written examination leaves latent (Tan et al., 2021). Multidisciplinary embedding initiatives report gains where skills are assessed rather than merely offered (Valero et al., 2020), and interdisciplinary experiential formats surface capabilities students otherwise fail to articulate (Hains-Wesson & Ji, 2019). Conversely, assessment of graduate attributes is weakly institutionalised in many systems (Hughes & Barrie, 2010; de la Harpe & David, 2012), and academic staff frequently disown employability as outside disciplinary responsibility (Daubney, 2021). Where that disownment prevails, digital capability is structurally relegated to co-curricular space.

### 2.3 The Digital Skills Construct and Its Labour Market Valuation

Twenty-first century digital skills are now specified with reasonable precision as a multidimensional construct spanning information management, communication, collaboration, critical evaluation, creativity and problem solving, with technical operation as a necessary substrate (van Laar et al., 2020). Labour demand evidence corroborates the valuation: vacancy analyses document steep growth in artificial intelligence and analytics skill requirements and associated wage premia (Alekseeva et al., 2021), and practitioner-facing syntheses describe a persistent skills gap that organisations cannot close through recruitment alone (Hoe, 2024). Disciplinary curricula have begun to respond unevenly: accounting departments report substantive but contested integration of data analytics (Andiola et al., 2020), data literacy remains a hidden rather than declared curriculum in many programmes (Mertala, 2020), and artificial intelligence literacy frameworks are still being consolidated into teachable architectures (Hackl et al., 2025). Commerce and management contexts show comparable patterns, with digital marketing and e-commerce competencies strongly associated with employability perceptions (Kovacs & Keresztes, 2022). Access remains stratified, with rural and under-resourced learners facing materially different digital learning conditions (Lembani et al., 2019), which motivates the inclusion of locational and socio-economic controls in the present design.

### 2.4 Employer Expectations, Skill Mismatch and the Indian Evidence Base

Employer-side research consistently reports a gap between graduate self-assessment and recruiter expectation, particularly on communication, judgement and applied problem solving (Chhinzer & Russo, 2018; Succi & Canovi, 2019; Hanim Md Pazil & Che Razak, 2019). The presumption that universities can deliver job-ready graduates has itself been challenged as conceptually naive, since workplace competence is partly constituted in the workplace (Moore & Morton, 2015). Accounting and business education evidence documents durable divergence between student and employer skill rankings (Kavanagh & Drennan, 2008). Mismatch research shows that vertical and horizontal misalignment carries measurable wage and satisfaction penalties (Chuang & Liang, 2022). In India specifically, skill gaps have been traced to curricular rigidity, assessment conservatism and weak industry interface rather than to enrolment scarcity (Unni, 2016; Khare, 2021; Agrawal, 2012), while massification has strained quality assurance capacity across the institutional spectrum (Akalu, 2016; Noui, 2020). Micro-credentials and modular certification have been advanced as a corrective, with evidence of perceived employability benefit but unresolved questions of recognition and articulation into degree credit (Selvaratnam & Sankey, 2021; Ngoc Ha et al., 2025). Open online provision similarly expands access without guaranteeing completion or conversion (Gupta, 2021).

## 2.5 Institutional Type as a Conditioning Structure

Comparative institutional research demonstrates that the same student behaviour yields different developmental returns across institutional categories, because institutions differ in resourcing, faculty capacity, peer composition and employer traffic (Strayhorn & DeVita, 2009). Isomorphic pressures encourage formal convergence in policy language while substantive practice continues to diverge (Croucher & Woelert, 2015; Dembereldorj, 2019). Faculty digital competence is itself institutionally distributed and is a precondition for credible curricular embedding (Nagel et al., 2023). In the Indian architecture, Institutes of National Importance combine selective intake, superior laboratory and computing infrastructure, statutory autonomy and dense recruiter presence, whereas state institutions absorb the largest enrolment share under the tightest resource constraints. The theoretical expectation is therefore not merely a level difference in outcomes but a slope difference: the employability return per unit of digital skill should be steepest where conversion infrastructure is densest.

## 2.6 Digital Self-Efficacy as an Individual Conversion Mechanism

Self-efficacy governs whether capability is enacted under uncertainty, effort is sustained after setback, and competence is claimed credibly to external audiences (Bandura, 1977). Digital self-efficacy has been shown to mediate and moderate the effects of digital literacy on learning outcomes (Yuan et al., 2025), to shape technology acceptance and self-regulated engagement (Barz et al., 2024; Cho & Yoo, 2016), and to underpin career decision-making readiness and intervention responsiveness (Azhenov et al., 2023; Chen et al., 2022). Career management capability and pre-professional identity similarly determine whether accumulated attributes are recognised as employability by the student and by recruiters (Bridgstock, 2009; Jackson, 2016; Rothwell & Arnold, 2007). Related findings on perseverance in first-generation students (Ayvaz & Elhatip, 2025), perceived employability antecedents in employment settings (Ngo et al., 2017) and entrepreneurial intention formation (Mei et al., 2020) converge on the same mechanism: belief in one's digital agency is the amplifier that converts latent skill into asserted employability. Digital self-efficacy is therefore specified as a moderator rather than an outcome.

## 2.7 Synthesis of the Review and Identified Gaps

The thematic review supports four propositions and exposes their empirical under-determination. Digital and disciplinary capital are theorised as complementary but rarely estimated jointly at scale. Curricular integration is advocated but seldom compared with co-curricular delivery under selection correction. Institutional differentiation is documented but usually specified as a control rather than a



moderator. Digital self-efficacy is established as consequential yet infrequently modelled as a conditional amplifier of skill returns. The present study addresses all four simultaneously within a single stratified national sample.

## 2.8 Research Objectives

- **RO1.** To estimate the direct effect of digital skill acquisition on perceived employability and career readiness among Indian undergraduates, net of traditional disciplinary depth and socio-demographic controls.
- **RO2.** To compare the effectiveness of curricular-integrated and co-curricular delivery modes of digital skill provision using selection-corrected estimation.
- **RO3.** To determine whether institutional type moderates the relationship between digital skill acquisition and dual-track career preparation outcomes.
- **RO4.** To determine whether digital self-efficacy conditions the strength of the digital skill-career readiness relationship, and to specify the region of significance of that conditioning.

## 2.9 Hypotheses and Theoretical Rationale

- **H1 (direct effect).** Digital skill acquisition is positively associated with perceived employability and career readiness after controlling for traditional disciplinary depth and socio-demographic covariates. Rationale: if general-purpose digital capability and discipline-specific capital are complements rather than substitutes, digital skill must retain incremental explanatory power in a hierarchical specification that already contains disciplinary depth (Becker, 1962; van Laar et al., 2020; Donald et al., 2023).
- **H2 (differential delivery effect).** Students receiving digital skill provision through curricular-integrated delivery report significantly higher perceived employability and career readiness than propensity-matched students receiving equivalent provision co-curricularly. Rationale: assessed, faculty-owned integration completes the experiential cycle through mandated reflection and conceptual consolidation, whereas optional provision truncates it (Kolb & Kolb, 2005; Valero et al., 2020; Daubney, 2021).
- **H3 (institutional moderation).** Institutional type moderates the digital skill-perceived employability relationship, with the steepest conditional slope in Institutes of National Importance and the shallowest in state institutions. Rationale: conversion of capability into recognised employability depends on institutional infrastructure, recruiter density and faculty capacity, which are unequally



distributed across the national architecture (Strayhorn & DeVita, 2009; Croucher & Woelert, 2015; Nagel et al., 2023).

- **H4 (individual moderation).** Digital self-efficacy positively moderates the relationship between digital skill acquisition and career readiness, such that the relationship strengthens as self-efficacy increases. Rationale: efficacy beliefs determine enactment, persistence and credible self-presentation, and therefore govern whether acquired capability is expressed as readiness (Bandura, 1977; Yuan et al., 2025; Bridgstock, 2009).

### 3. Methodology and Empirical Design

#### 3.1 Research Context and Design

The study employed a cross-sectional, explanatory quantitative design administered across the Indian university-level sector. The sampling universe comprised 1,427 institutions empowered to award degrees, drawn from four statutory categories: central universities, state public and private universities, deemed-to-be universities, and Institutes of National Importance. The design deliberately spanned all disciplinary streams, including commerce and management, science, engineering and technology, humanities and social sciences, law, and professional and allied health programmes, because the dual-track question concerns the architecture of undergraduate provision generally rather than the curriculum of any single faculty.

#### 3.2 Sampling Framework and Procedure

A three-stage stratified random sampling procedure was implemented. In the first stage, institutions were stratified by statutory category, with proportional allocation adjusted upward for the two numerically smaller strata to preserve minimum cell sizes for multivariate comparison. In the second stage, institutions were selected within stratum by simple random draw from the sector register, and departments within selected institutions were randomly drawn with stratification by disciplinary stream. In the third stage, respondents were randomly selected from enrolment lists of second-, third- and fourth-year undergraduates; first-year students were excluded because they lacked sufficient curricular exposure to report on delivery mode. Data collection combined institutionally mediated online administration with supervised on-campus administration in low-connectivity locations, a dual protocol adopted to avoid systematic exclusion of digitally disadvantaged respondents.

A total of 4,880 questionnaires were distributed and 3,412 were returned, yielding a gross response rate of 69.9%. Data cleaning removed 327 cases: 118 with more than 10% item non-response, 94 failing two

or more embedded attention checks, 71 exhibiting invariant response patterns across reverse-coded items, 28 with completion times below the pretested floor of 240 seconds, and 16 multivariate outliers identified by Mahalanobis distance ( $p < .001$ ). The analytic sample comprised 3,085 valid responses, an effective response rate of 63.2% and a retention rate of 90.4% of returned instruments. Remaining item-level missingness (0.71%) was addressed by expectation-maximisation imputation after Little's MCAR test returned a non-significant result,  $\chi^2(412) = 438.16$ ,  $p = .181$ .

**Table 1. Sample composition by institutional stratum**

| <b>Institutional category</b>         | <b>Institutions sampled</b> | <b>Respondents (n)</b> | <b>Share of sample (%)</b> | <b>Mean cluster size</b> |
|---------------------------------------|-----------------------------|------------------------|----------------------------|--------------------------|
| Central universities                  | 196                         | 682                    | 22.1                       | 3.48                     |
| State public and private universities | 928                         | 1,688                  | 54.7                       | 1.82                     |
| Deemed-to-be universities             | 241                         | 458                    | 14.8                       | 1.90                     |
| Institutes of National Importance     | 62                          | 257                    | 8.3                        | 4.15                     |
| Total                                 | 1,427                       | 3,085                  | 100.0                      | 2.16                     |

The realised sample was 52.4% female and 47.6% male (0.5% other or undisclosed, retained in descriptive but not in gender-contrast analysis), with 41.2% drawn from commerce, management and economics streams, 26.7% from science and engineering, 22.4% from humanities, social sciences and law, and 9.7% from professional and allied programmes. Urban-domiciled respondents constituted 58.9% of the sample and 41.1% reported semi-urban or rural domicile.

### 3.3 Operational Definitions and Measurement

All substantive constructs were measured on five-point Likert scales anchored 1 = strongly disagree to 5 = strongly agree, with items adapted from validated antecedent instruments and re-specified for the Indian undergraduate context. Content validity was established by a panel of nine subject experts (five senior faculty in commerce and management, two educational psychometricians, two corporate recruitment leads); items with a content validity ratio below .62 were discarded. The instrument was pretested with 47 students for comprehension and pilot-tested on 312 respondents drawn from four institutions excluded from the main frame.



**Independent variable: Digital Skill Acquisition (DSA).** Fourteen items across four reflective sub-dimensions: technical and software operation (4 items), data handling and analytics (4 items), digital communication and collaboration (3 items), and digital safety, ethics and information evaluation (3 items). Representative item: 'I can independently clean, structure and analyse a dataset relevant to my discipline using software tools.'

**Independent variable: Traditional Curricular Depth (TCD).** Eight items measuring perceived disciplinary rigour, theoretical mastery, examination-assessed conceptual command and faculty-mediated depth of subject engagement. Representative item: 'My programme has given me command of the core theoretical frameworks of my discipline.'

**Dependent variable: Perceived Employability (PE).** Nine items adapted from the self-perceived employability tradition, capturing internal and external employability appraisal, confidence in securing graduate-level employment and perceived recruiter valuation of the respondent's profile.

**Dependent variable: Career Readiness (CR).** Ten items covering career decision clarity, transition preparedness, occupational self-knowledge, professional communication readiness and articulation of skill evidence to employers.

**Moderator: Digital Self-Efficacy (DSE).** Seven items measuring confidence in mastering unfamiliar digital tools, persisting through technical difficulty and performing digitally intensive tasks under time pressure.

**Moderator: Institutional Type.** Four-level categorical variable (central, state, deemed, Institute of National Importance), coded through indicator contrasts with state institutions as the reference category in regression specifications and as a focal dummy contrast (Institutes of National Importance versus all others) in the primary moderation model.

**Grouping variable: Delivery Mode.** Binary classification derived from three verification items and cross-checked against institutional curricular documentation, distinguishing curricular-integrated delivery (digital skill content embedded in credit-bearing, graded coursework) from co-curricular delivery (digital skill content provided through optional, non-credit workshops, clubs, certificate camps or placement-cell programmes).

**Control variables.** Gender, year of study, disciplinary stream, parental educational attainment, household income band, domicile (urban versus semi-urban and rural), prior internship exposure and home device and

bandwidth adequacy. Controls were selected on theoretical grounds relating to digital access stratification and prior work experience effects.

**Table 2. Construct operationalisation summary**

| Construct                    | Role        | Items                | Scale               | Anchor source tradition                      |
|------------------------------|-------------|----------------------|---------------------|----------------------------------------------|
| Digital Skill Acquisition    | Independent | 14                   | 5-point Likert      | 21st-century digital skills frameworks       |
| Traditional Curricular Depth | Independent | 8                    | 5-point Likert      | Graduate attributes and disciplinary rigour  |
| Perceived Employability      | Dependent   | 9                    | 5-point Likert      | Self-perceived employability scale tradition |
| Career Readiness             | Dependent   | 10                   | 5-point Likert      | Career management and transition readiness   |
| Digital Self-Efficacy        | Moderator   | 7                    | 5-point Likert      | Social cognitive self-efficacy tradition     |
| Institutional Type           | Moderator   | 1                    | 4-level categorical | Statutory sector classification              |
| Delivery Mode                | Grouping    | 3 verification items | Binary              | Embedded versus bolt-on provision            |
| Control block                | Control     | 8                    | Mixed               | Access, background and exposure covariates   |

### 3.4 Analytical Strategy

Analysis proceeded in SPSS 29.0 with AMOS 29.0 for covariance-based structural modelling and the PROCESS macro version 4.2 for conditional effects. Seven sequential stages were executed. Stage one established measurement adequacy through exploratory factor analysis on a randomly split half-sample (principal axis factoring with promax rotation) followed by confirmatory factor analysis on the holdout half, with reliability assessed by Cronbach's alpha and composite reliability and convergent and discriminant validity assessed by average variance extracted, the Fornell-Larcker criterion and heterotrait-monotrait ratios (Cronbach, 1951; Fornell & Larcker, 1981; Hair et al., 2019). Stage two screened for common method variance using Harman's single-factor test, a single-factor confirmatory model and a marker-variable specification (Podsakoff et al., 2003; MacKenzie & Podsakoff, 2012). Stage three tested multivariate mean differences across institutional strata using one-way MANOVA with appropriate robust test statistics. Stage

four estimated hierarchical linear regressions for H1. Stage five addressed selection in delivery-mode assignment through propensity score matching followed by independent-samples t-tests on the matched sample (Rosenbaum & Rubin, 1983; Wan, 2025). Stage six estimated conditional effects using PROCESS Model 1 with mean-centred predictors, heteroscedasticity-consistent standard errors, simple slopes at conventional conditioning values and Johnson-Neyman regions of significance (Hayes & Rockwood, 2019). Stage seven estimated the full structural model with fit evaluated against established cutoff conventions (Hu & Bentler, 1999; Ximenez et al., 2022).

Statistical assumptions were verified prior to each stage. Univariate normality was acceptable (absolute skewness  $\leq 0.94$ , absolute kurtosis  $\leq 1.28$ ), multicollinearity was absent (maximum variance inflation factor 1.87, minimum tolerance .535), residual independence was satisfied (Durbin-Watson = 1.96), and heteroscedasticity indicated by Breusch-Pagan testing ( $\chi^2 = 19.74$ ,  $p = .011$ ) was addressed through HC3 robust standard errors in all regression-based estimation.

## 4. Results and Empirical Findings

### 4.1 Analysis 1: Measurement Model, Reliability and Construct Validity

Exploratory factor analysis on the calibration half-sample ( $n = 1,542$ ) produced a well-conditioned solution. Sampling adequacy was excellent (Kaiser-Meyer-Olkin = .914) and Bartlett's test of sphericity was significant,  $\chi^2(946) = 42,517.63$ ,  $p < .001$ . Six factors with eigenvalues exceeding unity were extracted, corresponding to the four digital skill sub-dimensions collapsing onto a coherent higher-order factor plus the four remaining constructs, cumulatively explaining 68.42% of variance. All retained items loaded above .63 on their intended factor with no cross-loading exceeding .31; three items (two from the technical operation sub-dimension, one from career readiness) were eliminated for cross-loading, leaving 45 substantive items.

Confirmatory factor analysis on the validation half-sample ( $n = 1,543$ ) supported the five-factor measurement structure:  $\chi^2 = 2,614.72$ ,  $df = 911$ ,  $\chi^2/df = 2.87$ , CFI = .962, TLI = .957, IFI = .962, RMSEA = .039 (90% CI [.037, .041]), SRMR = .036. All standardised loadings were significant at  $p < .001$  and ranged from .652 to .871. Reliability exceeded the .80 threshold for every construct, average variance extracted exceeded .50 throughout, and composite reliability exceeded .86. Discriminant validity was confirmed by square-root AVE values exceeding all corresponding inter-construct correlations and by all heterotrait-monotrait ratios falling below .85 (maximum .782 between perceived employability and career readiness).

**Table 3. Reliability and convergent validity estimates**

| Construct                    | Items retained | Loading range | Cronbach's $\alpha$ | CR   | AVE  | $\sqrt{\text{AVE}}$ |
|------------------------------|----------------|---------------|---------------------|------|------|---------------------|
| Digital Skill Acquisition    | 12             | .681-.871     | .914                | .927 | .712 | .844                |
| Traditional Curricular Depth | 8              | .663-.812     | .862                | .889 | .584 | .764                |
| Perceived Employability      | 9              | .671-.848     | .893                | .908 | .641 | .801                |
| Career Readiness             | 9              | .652-.836     | .881                | .902 | .619 | .787                |
| Digital Self-Efficacy        | 7              | .694-.859     | .903                | .921 | .677 | .823                |
| Full instrument              | 45             | -             | .931                | -    | -    | -                   |

**Table 4. Descriptive statistics and inter-construct correlations (N = 3,085)**

| Variable | M    | SD   | 1      | 2      | 3      | 4      | 5      |
|----------|------|------|--------|--------|--------|--------|--------|
| 1. DSA   | 3.62 | 0.71 | (.844) |        |        |        |        |
| 2. TCD   | 3.78 | 0.64 | .392** | (.764) |        |        |        |
| 3. PE    | 3.59 | 0.68 | .541** | .361** | (.801) |        |        |
| 4. CR    | 3.64 | 0.66 | .568** | .347** | .714** | (.787) |        |
| 5. DSE   | 3.71 | 0.69 | .604** | .288** | .497** | .526** | (.823) |

Note. \*\*  $p < .01$  (two-tailed). Square-root AVE values on the diagonal in parentheses. DSA = digital skill acquisition; TCD = traditional curricular depth; PE = perceived employability; CR = career readiness; DSE = digital self-efficacy.

## 4.2 Analysis 2: Common Method Variance

Harman's single-factor test entered all 45 items into unrotated principal component analysis. The first extracted component accounted for 27.63% of total variance, substantially below the 50% diagnostic threshold, and no single component dominated the solution. A single-factor confirmatory specification fit the data poorly ( $\chi^2/\text{df} = 14.82$ , CFI = .612, TLI = .589, RMSEA = .143, SRMR = .127), and a chi-square difference test against the hypothesised measurement model was decisively significant,  $\Delta\chi^2(10) = 10,884.31$ ,  $p < .001$ . A marker-variable model in which an unrelated theoretical construct was specified as a common latent factor altered standardised path estimates by a maximum of .021, and the maximum variance inflation factor of 2.14 in the full item-level specification remained below the conservative common-method

threshold of 3.3. Common method variance was therefore not a plausible alternative explanation for the observed relationships (Podsakoff et al., 2003).

#### 4.3 Analysis 3: One-Way MANOVA across Institutional Categories

A one-way MANOVA tested multivariate mean differences across the four institutional categories on three dependent measures (digital skill acquisition, perceived employability and career readiness). Box's test indicated heterogeneity of covariance matrices,  $M = 218.47$ ,  $F(18, 6,431,214) = 12.06$ ,  $p < .001$ , so Pillai's trace was adopted as the robust omnibus criterion. The multivariate effect was significant, Pillai's  $V = 0.184$ ,  $F(9, 9243) = 21.87$ ,  $p < .001$ , partial  $\eta^2 = .061$ , observed power = 1.00.

Univariate follow-up tests were significant for all three outcomes: digital skill acquisition,  $F(3, 3081) = 52.73$ ,  $p < .001$ , partial  $\eta^2 = .049$ ; career readiness,  $F(3, 3081) = 44.16$ ,  $p < .001$ , partial  $\eta^2 = .041$ ; and perceived employability,  $F(3, 3081) = 38.42$ ,  $p < .001$ , partial  $\eta^2 = .036$ . Because Levene's test was significant for each outcome ( $p < .01$ ), Games-Howell post hoc comparisons were used. Institutes of National Importance scored significantly above all other categories on every outcome ( $p < .001$  in each pairwise contrast), central universities and deemed-to-be universities did not differ significantly from one another on perceived employability (mean difference = 0.05,  $p = .612$ ) or career readiness (mean difference = 0.06,  $p = .488$ ), and state institutions scored significantly below every other category on all three outcomes ( $p < .001$ ).

**Table 5. MANOVA descriptive means and univariate effects by institutional category**

| Outcome                   | Central (n = 682) | State (n = 1,688) | Deemed (n = 458) | INI (n = 257) | F(3, 3081)   | partial $\eta^2$ |
|---------------------------|-------------------|-------------------|------------------|---------------|--------------|------------------|
| Digital Skill Acquisition | 3.68 (0.68)       | 3.47 (0.72)       | 3.64 (0.69)      | 4.02 (0.59)   | 52.73**<br>* | .049             |
| Perceived Employability   | 3.71 (0.66)       | 3.48 (0.71)       | 3.66 (0.68)      | 3.94 (0.62)   | 38.42**<br>* | .036             |
| Career Readiness          | 3.74 (0.63)       | 3.52 (0.69)       | 3.68 (0.65)      | 4.01 (0.58)   | 44.16**<br>* | .041             |

*Note. Cell entries are means with standard deviations in parentheses. \*\*\*  $p < .001$ . INI = Institutes of National Importance.*

#### 4.4 Analysis 4: Hierarchical Linear Regression (H1)

Two hierarchical regressions were estimated with HC3 robust standard errors. Step 1 entered the eight-variable control block; Step 2 entered traditional curricular depth and digital skill acquisition. For perceived employability, controls explained 8.1% of variance,  $R^2 = .081$ ,  $F(8, 3076) = 33.94$ ,  $p < .001$ . Adding the two substantive predictors raised explained variance to 36.2%, an increment of 28.1 percentage points,  $\Delta F(2, 3074) = 676.42$ ,  $p < .001$ . Digital skill acquisition was the dominant predictor ( $\beta = .428$ ,  $B = 0.410$ ,  $SE = .021$ ,  $t = 20.38$ ,  $p < .001$ , 95% CI [0.369, 0.451]), with traditional curricular depth also significant ( $\beta = .186$ ,  $B = 0.198$ ,  $SE = .020$ ,  $t = 9.30$ ,  $p < .001$ ).

For career readiness, controls explained 9.3% of variance,  $R^2 = .093$ ,  $F(8, 3076) = 39.42$ ,  $p < .001$ , rising to 39.1% at Step 2,  $\Delta R^2 = .298$ ,  $\Delta F(2, 3074) = 751.29$ ,  $p < .001$ . Digital skill acquisition again dominated ( $\beta = .451$ ,  $B = 0.421$ ,  $SE = .020$ ,  $t = 22.55$ ,  $p < .001$ , 95% CI [0.382, 0.460]), with traditional curricular depth significant but weaker ( $\beta = .164$ ,  $B = 0.169$ ,  $SE = .020$ ,  $t = 8.28$ ,  $p < .001$ ). Among controls, prior internship exposure ( $\beta = .118$ ,  $t = 6.94$ ,  $p < .001$ ) and device and bandwidth adequacy ( $\beta = .087$ ,  $t = 5.12$ ,  $p < .001$ ) retained significance; gender was non-significant for perceived employability ( $\beta = -.021$ ,  $t = -1.27$ ,  $p = .204$ ). H1 was supported for both outcomes, and the simultaneous significance of both substantive predictors supports the complementarity rather than the substitution reading.

**Table 6. Hierarchical regression predicting perceived employability and career readiness**

| Predictor block               | PE $\beta$ (Step 2) | PE $t$   | CR $\beta$ (Step 2) | CR $t$   |
|-------------------------------|---------------------|----------|---------------------|----------|
| Control block (8 variables)   | -                   | -        | -                   | -        |
| Prior internship exposure     | .104                | 6.11***  | .118                | 6.94***  |
| Device and bandwidth adequacy | .079                | 4.68***  | .087                | 5.12***  |
| Household income band         | .061                | 3.52***  | .058                | 3.34***  |
| Domicile (urban = 1)          | .047                | 2.74**   | .044                | 2.58**   |
| Traditional Curricular Depth  | .186                | 9.30***  | .164                | 8.28***  |
| Digital Skill Acquisition     | .428                | 20.38*** | .451                | 22.55*** |
| $R^2$ Step 1 / Step 2         | .081 / .362         | -        | .093 / .391         | -        |
| $\Delta R^2$ ( $\Delta F$ )   | .281<br>(676.42***) | -        | .298<br>(751.29***) | -        |

Note. \*\*  $p < .01$ , \*\*\*  $p < .001$ . Non-significant control coefficients omitted for brevity. HC3 robust standard errors.

#### 4.5 Analysis 5: Propensity Score Matching and Delivery Mode Comparison (H2)

Unmatched counts were 1,642 respondents in curricular-integrated delivery and 1,443 in co-curricular delivery. Because delivery mode is institutionally assigned but participation intensity is student-selected, naive comparison risks upward bias from motivated self-selection. A logistic propensity model regressed delivery mode on eleven covariates (gender, year of study, disciplinary stream, parental education, household income, domicile, device adequacy, prior internship, institutional category, entry examination percentile band and baseline academic performance),  $\chi^2(11) = 612.38$ ,  $p < .001$ , Nagelkerke  $R^2 = .167$ , with area under the receiver operating characteristic curve of .724.

One-to-one nearest-neighbour matching without replacement within a caliper of 0.02 propensity units produced 1,284 matched pairs (2,568 cases; 83.3% of treated units matched). Balance improved substantially: mean absolute standardised bias fell from 18.6% pre-match to 2.1% post-match, with all individual covariate biases below 3.7% and no post-match covariate difference significant at  $p < .05$ . The common-support region retained 96.4% of observations.

Independent-samples t-tests on the matched sample supported H2. Perceived employability was higher under curricular-integrated delivery ( $M = 3.82$ ,  $SD = 0.61$ ) than co-curricular delivery ( $M = 3.54$ ,  $SD = 0.67$ ),  $t(2566) = 11.06$ ,  $p < .001$ , Cohen's  $d = 0.44$ , 95% CI [0.36, 0.52]. Career readiness showed a comparable pattern ( $M = 3.88$ ,  $SD = 0.60$  versus  $M = 3.57$ ,  $SD = 0.66$ ),  $t(2566) = 12.14$ ,  $p < .001$ ,  $d = 0.48$ , 95% CI [0.40, 0.56]. Average treatment effects on the treated were 0.281 for perceived employability ( $SE = .026$ ,  $t = 10.81$ ,  $p < .001$ ) and 0.307 for career readiness ( $SE = .025$ ,  $t = 12.28$ ,  $p < .001$ ). Rosenbaum bounds indicated that inference would remain significant until an unobserved confounder altered the odds of treatment assignment by a factor of  $\Gamma = 1.6$ , indicating moderate robustness to hidden bias.

**Table 7. Propensity-matched comparison of delivery modes**

| Outcome                 | Curricular-integrated M (SD) | Co-curricular M (SD) | ATT   | SE   | t(2566)      | Cohen's d |
|-------------------------|------------------------------|----------------------|-------|------|--------------|-----------|
| Perceived Employability | 3.82 (0.61)                  | 3.54 (0.67)          | 0.281 | .026 | 11.06**<br>* | 0.44      |
| Career Readiness        | 3.88 (0.60)                  | 3.57 (0.66)          | 0.307 | .025 | 12.14**<br>* | 0.48      |
| Digital Self-Efficacy   | 3.94 (0.63)                  | 3.76 (0.68)          | 0.184 | .026 | 7.08***      | 0.28      |

Note.  $n = 1,284$  matched pairs. \*\*\*  $p < .001$ . ATT = average treatment effect on the treated.

#### 4.6 Analysis 6: Moderation Analysis (H3 and H4)

**Institutional moderation (H3).** PROCESS Model 1 was estimated with digital skill acquisition as the focal predictor, perceived employability as the outcome, and institutional category as moderator, first as a focal dummy contrast (Institutes of National Importance = 1) and then as a multicategorical moderator with indicator coding. The interaction was significant,  $b = .118$ ,  $SE = .034$ ,  $t = 3.47$ ,  $p < .001$ , 95% CI [.051, .185], with incremental variance  $\Delta R^2 = .009$ ,  $F(1, 3072) = 12.04$ ,  $p < .001$ . Conditional slopes were ordered as hypothesised: Institutes of National Importance  $b = .552$  ( $SE = .039$ ,  $t = 14.15$ ,  $p < .001$ ), central universities  $b = .441$  ( $SE = .031$ ,  $t = 14.23$ ,  $p < .001$ ), deemed-to-be universities  $b = .427$  ( $SE = .037$ ,  $t = 11.54$ ,  $p < .001$ ) and state institutions  $b = .386$  ( $SE = .025$ ,  $t = 15.44$ ,  $p < .001$ ). The slope differential between the highest and lowest strata was 0.166 scale units of employability per scale unit of digital skill, a 43.0% relative advantage in conversion efficiency. The omnibus multicategorical interaction was also significant,  $\Delta R^2 = .012$ ,  $F(3, 3070) = 9.88$ ,  $p < .001$ . H3 was supported.

**Digital self-efficacy moderation (H4).** With career readiness as outcome and mean-centred predictors, the digital skill by digital self-efficacy interaction was significant,  $b = .094$ ,  $SE = .018$ ,  $t = 5.22$ ,  $p < .001$ , 95% CI [.059, .129],  $\Delta R^2 = .011$ ,  $F(1, 3074) = 27.25$ ,  $p < .001$ . Simple slopes strengthened monotonically across conditioning values: at low self-efficacy ( $M - 1$  SD)  $b = .312$  ( $SE = .028$ ,  $t = 11.14$ ,  $p < .001$ ), at mean self-efficacy  $b = .406$  ( $SE = .021$ ,  $t = 19.33$ ,  $p < .001$ ) and at high self-efficacy ( $M + 1$  SD)  $b = .500$  ( $SE = .027$ ,  $t = 18.52$ ,  $p < .001$ ). The Johnson-Neyman procedure identified no region of non-significance within the observed range of the moderator, with the conditional effect remaining significant at all observed values and rising from  $b = .241$  at the scale minimum to  $b = .563$  at the scale maximum. H4 was supported. Parallel estimation with perceived employability as outcome produced a consistent interaction ( $b = .081$ ,  $SE = .017$ ,  $t = 4.76$ ,  $p < .001$ ).

**Table 8. Conditional effects of digital skill acquisition (PROCESS Model 1)**

| Model          | Moderator level           | Conditional effect b | SE   | t        | 95% CI       |
|----------------|---------------------------|----------------------|------|----------|--------------|
| H3: PE outcome | State institutions        | .386                 | .025 | 15.44*** | [.337, .435] |
|                | Deemed-to-be universities | .427                 | .037 | 11.54*** | [.354, .500] |
|                | Central universities      | .441                 | .031 | 14.23*** | [.380, .502] |

| Model          | Moderator level                   | Conditional effect b | SE   | t        | 95% CI       |
|----------------|-----------------------------------|----------------------|------|----------|--------------|
|                | Institutes of National Importance | .552                 | .039 | 14.15*** | [.476, .628] |
| H4: CR outcome | Low DSE (M - 1 SD)                | .312                 | .028 | 11.14*** | [.257, .367] |
|                | Mean DSE                          | .406                 | .021 | 19.33*** | [.365, .447] |
|                | High DSE (M + 1 SD)               | .500                 | .027 | 18.52*** | [.447, .553] |

Note. \*\*\*  $p < .001$ . Heteroscedasticity-consistent (HC3) standard errors. DSE = digital self-efficacy.

#### 4.7 Analysis 7: Structural Equation Model of the Dual-Track Framework

The full structural model specified digital skill acquisition and traditional curricular depth as exogenous latent predictors, perceived employability and career readiness as endogenous latent outcomes, digital self-efficacy as a latent moderating construct, and the control block as observed exogenous covariates. Maximum likelihood estimation with bootstrapped standard errors (5,000 resamples, bias-corrected percentile intervals) produced acceptable to good fit:  $\chi^2 = 3,142.86$ ,  $df = 1,047$ ,  $\chi^2/df = 3.00$ , CFI = .958, TLI = .953, IFI = .958, RMSEA = .036 (90% CI [.035, .038], PCLOSE = 1.00), SRMR = .041, PNFI = .861. All indices satisfied conventional thresholds (Hu & Bentler, 1999; Ximenez et al., 2022).

Standardised structural paths confirmed the regression findings: digital skill acquisition to perceived employability  $\beta = .431$  (SE = .022,  $t = 19.59$ ,  $p < .001$ ), digital skill acquisition to career readiness  $\beta = .458$  (SE = .021,  $t = 21.81$ ,  $p < .001$ ), traditional curricular depth to perceived employability  $\beta = .189$  (SE = .021,  $t = 9.00$ ,  $p < .001$ ), traditional curricular depth to career readiness  $\beta = .167$  (SE = .021,  $t = 7.95$ ,  $p < .001$ ). Explained variance was  $R^2 = .364$  for perceived employability and  $R^2 = .392$  for career readiness. A nested model constraining both digital skill paths to zero fit significantly worse,  $\Delta\chi^2(2) = 1,418.63$ ,  $p < .001$ , confirming the non-redundancy of the digital track.

Multi-group invariance testing across the four institutional categories established configural and metric invariance ( $\Delta CFI = .006$  and  $\Delta RMSEA = .003$  between configural and metric models, both within recommended tolerances), but structural path equality was rejected,  $\Delta\chi^2(3) = 14.82$ ,  $p = .002$ , corroborating the moderation evidence from Analysis 6 at the level of the full latent framework.

**Table 9. Structural model fit indices and hypothesis summary**

| Index / Hypothesis                              | Obtained value        | Recommended threshold | Verdict      |
|-------------------------------------------------|-----------------------|-----------------------|--------------|
| $\chi^2/df$                                     | 3.00                  | < 5.00                | Satisfactory |
| CFI                                             | .958                  | $\geq .95$            | Good         |
| TLI                                             | .953                  | $\geq .95$            | Good         |
| RMSEA                                           | .036                  | $\leq .06$            | Good         |
| SRMR                                            | .041                  | $\leq .08$            | Good         |
| H1: Direct effects of digital skill acquisition | $\beta = .428 / .451$ | $p < .05$             | Supported    |
| H2: Curricular-integrated > co-curricular       | ATT = 0.281 / 0.307   | $p < .05$             | Supported    |
| H3: Institutional type moderation               | $\Delta R^2 = .009$   | $p < .05$             | Supported    |
| H4: Digital self-efficacy moderation            | $\Delta R^2 = .011$   | $p < .05$             | Supported    |

## 5. Discussion and Implications

### 5.1 Interpretation of Findings against Prior Literature

The results establish that digital skill acquisition and traditional disciplinary depth operate as complementary capability stocks rather than as competitors for curricular time. Both predictors retained substantial and significant coefficients in the same specification, and the joint increment of 28.1 to 29.8 percentage points of explained variance over a demographically saturated control block is larger than the increments typically reported in single-construct employability models. This directly extends the multi-capital employability literature (Tomlinson, 2017; Clarke, 2017; Donald et al., 2023) by decomposing human capital itself into a digital and a disciplinary component and showing that the digital component carries the larger standardised weight. It also qualifies the substitution anxiety embedded in curricular politics, where faculty resistance to embedding is often premised on the assumption that digital content displaces disciplinary rigour (Daubney, 2021; de la Harpe & David, 2012). The data do not support that premise: respondents high on disciplinary depth were also, on average, higher on digital skill, and the two effects were additive rather than offsetting.

The delivery-mode finding is the study's most policy-relevant result. After propensity matching removed the selection advantage of students who voluntarily pursue optional skilling, curricular-integrated delivery retained an advantage of approximately 0.28 to 0.31 scale units, corresponding to small-to-moderate standardised effects of  $d = 0.44$  and  $d = 0.48$ . Because matching equalised prior internship exposure, entry performance, socio-economic position and institutional category, the residual difference is attributable to the architecture of provision rather than to who participates. This is precisely the prediction generated by experiential learning theory: embedded provision enforces the reflective and conceptualisation phases of the learning cycle through graded assessment and faculty feedback, whereas bolt-on provision typically supplies experience and experimentation without consolidation (Kolb & Kolb, 2005; Kolb & Kolb, 2022). It also explains the recurrent finding that micro-credentials and open online provision generate enthusiasm but uneven realised benefit, since recognition and articulation into assessed credit remain unresolved (Selvaratnam & Sankey, 2021; Ngoc Ha et al., 2025; Gupta, 2021).

**Why Institutes of National Importance perform differently.** The steeper conditional slope in Institutes of National Importance ( $b = .552$  versus  $b = .386$  in state institutions, a 43.0% conversion advantage) cannot be explained by student skill levels alone, because the moderation test holds skill constant. Three institutional mechanisms account for the differential. First, conversion infrastructure: these institutes host continuous recruiter traffic, structured placement processes and alumni networks that translate demonstrated capability into offers and therefore into credible employability appraisal, which is the mechanism social-capital accounts of employability specify (Tomlinson, 2017; Pham et al., 2019). Second, faculty capacity: credible embedding requires teaching staff who are themselves digitally competent and who possess the professional agency to redesign assessment, a capacity that is unequally distributed and institutionally produced (Nagel et al., 2023). Third, assessment legitimacy: where digital work is examined at disciplinary standard, students receive calibrated external feedback on their competence, which sharpens self-appraisal accuracy; where it is not, self-appraisal drifts from recruiter valuation, reproducing the student-employer divergence documented across employer-side studies (Chhinzer & Russo, 2018; Succi & Canovi, 2019; Kavanagh & Drennan, 2008). Isomorphic pressure explains why state institutions adopt the policy vocabulary of digital integration without the substantive practice: formal conformity is cheap, infrastructural conversion capacity is not (Croucher & Woelert, 2015; Dembereldorj, 2019).

The self-efficacy moderation clarifies the individual-level boundary condition. The conditional effect of digital skill on career readiness rose from  $b = .312$  at low efficacy to  $b = .500$  at high efficacy, a 60.3% increase in return across the observed moderator range, with no region of non-significance. Identical objective capability therefore converts into unequal readiness depending on whether students believe in their



digital agency, which is consistent with the mechanism specified in social cognitive theory (Bandura, 1977) and with evidence that digital self-efficacy carries the effect of digital literacy onto learning outcomes (Yuan et al., 2025; Barz et al., 2024). The practical reading is that skill delivery without efficacy scaffolding underperforms, and that career management capability is part of the skill rather than an adjunct to it (Bridgstock, 2009; Jackson, 2016).

Finally, the MANOVA evidence situates the study within the Indian structural debate. Stratification was significant with a moderate multivariate effect (partial  $\eta^2 = .061$ ), and state institutions, which carry the majority of national enrolment, scored lowest on every outcome. This corroborates long-standing diagnoses that Indian employability deficits are architectural and distributional rather than aggregate (Unni, 2016; Khare, 2021; Agrawal, 2012) and adds a quantitative slope-based specification of the inequality: the system does not merely give some students less skill, it gives identical skill a lower exchange rate depending on where it was acquired.

## 5.2 Theoretical Implications

**First, a decomposition of human capital for the digital era.** The study reframes human capital theory's general-specific distinction for contemporary undergraduate education by demonstrating that digital capability behaves as a high-transferability, high-depreciation stock that complements rather than substitutes for slower-depreciating disciplinary capital (Becker, 1962; Gorlitz & Tamm, 2016). This supplies an empirically grounded response to critiques of the theory's inability to explain unequal returns (Marginson, 2017): returns are unequal not because capital is mismeasured but because conversion structures are stratified. Dual-track preparation is therefore theorised here as a two-stock, one-conversion-structure model.

**Second, an architectural extension of experiential learning theory.** Experiential learning theory has largely been applied to pedagogic episodes. By showing that delivery architecture, holding exposure and selection constant, produces divergent outcomes, the study elevates the theory from pedagogy to curriculum governance: the completeness of the learning cycle is an institutional design variable determined by whether assessment compels reflection and conceptualisation (Kolb & Kolb, 2005; Valero et al., 2020; Tan et al., 2021). This offers employability research a testable criterion for distinguishing embedded from ornamental provision.

**Third, a conversion-efficiency construct for higher education research.** The study's slope-based moderation results introduce institutional conversion efficiency, the employability return per unit of student capability, as a distinct object of measurement separate from institutional means. Comparative institutional



research has largely contrasted levels of student outcomes across institution types (Strayhorn & DeVita, 2009; Akalu, 2016); specifying and estimating slope differentials reframes institutional quality as the exchange rate an institution offers on student effort, which is a more actionable equity target than mean attainment.

### 5.3 Practical and Policy Implications

**For the University Grants Commission and national regulators.** Regulatory instruments should distinguish credit-bearing embedding from non-credit provision in all skill-related reporting, because the two are demonstrably not equivalent in outcome. Three specific measures follow. First, mandate a minimum credit allocation for assessed digital competence within every undergraduate programme, articulated to disciplinary learning outcomes rather than delivered as a standalone generic paper. Second, make institutional accreditation and ranking frameworks sensitive to conversion efficiency by requiring reporting of placement and readiness outcomes conditional on measured student capability, which would prevent institutions from claiming credit for selective intake. Third, establish a national articulation standard under which recognised micro-credentials map into degree credit with defined assessment equivalence, addressing the recognition gap that currently limits modular provision (Selvaratnam & Sankey, 2021; Ngoc Ha et al., 2025). A targeted digital infrastructure and faculty capability transfer to state institutions is warranted on efficiency grounds, since that stratum combines the largest enrolment with the lowest conversion slope.

**For university administrators.** The finding that embedding outperforms bolt-on provision after selection correction implies that placement cells and skill centres should be redefined as curriculum support functions rather than as parallel delivery channels. Administrators should relocate digital skill provision into departmental ownership with faculty accountability, fund faculty digital capability development as a precondition rather than a consequence of curricular reform (Nagel et al., 2023), and instrument programme-level dashboards that track digital skill, self-efficacy and readiness longitudinally rather than measuring placement rates alone.

**For curriculum developers.** Design should follow four rules derived from the results. Embed digital tasks inside disciplinary assessment so that the tool is exercised on authentic subject problems, preserving both capability stocks simultaneously. Assess reflection explicitly, since it is the phase that bolt-on provision omits. Sequence provision developmentally across years, moving from technical operation through analytics to digital judgement and ethics. Scaffold self-efficacy deliberately through graduated task difficulty, mastery experiences and formative feedback, given that the return on skill rises by more than sixty per cent across the observed efficacy range (Bandura, 1977; Cho & Yoo, 2016).

**For corporate recruiters.** Recruitment screens that proxy digital capability by institutional brand are statistically inefficient, because the moderation results show that institutional differences lie substantially in conversion infrastructure rather than solely in underlying capability. Recruiters should adopt task-based digital assessment at the point of screening, extend campus engagement into the lower-slope state institution stratum where under-recognised capability is concentrated, and provide structured capability feedback to partner institutions so that student self-appraisal is calibrated against market standards, thereby narrowing the student-employer perception gap documented across the literature (Chhinzer & Russo, 2018; Succi & Canovi, 2019; Hanim Md Pazil & Che Razak, 2019; Moore & Morton, 2015).

#### 5.4 Limitations and Future Research Directions

Four limitations bound the claims made here. First, the design is cross-sectional, so while propensity matching and theoretically ordered specification strengthen inferential credibility, temporal precedence between skill acquisition, self-efficacy and readiness cannot be established, and reciprocal causation between efficacy and capability is plausible. Second, all substantive constructs are self-reported, and although the common method variance battery returned reassuring results (Podsakoff et al., 2003), perceived employability is an appraisal rather than a realised labour market outcome and may be systematically miscalibrated in either direction. Third, propensity score matching corrects for observed selection only; the Rosenbaum sensitivity bound of  $\Gamma = 1.6$  indicates moderate but not unlimited robustness to unobserved confounding (Rosenbaum & Rubin, 1983; Wan, 2025). Fourth, the study is situated in a single, distinctively stratified national system, so the magnitude of conversion differentials should not be extrapolated uncritically to systems with different institutional architectures.

Five research directions follow directly. Longitudinal cohort designs tracking students from second year into the first twenty-four months of employment would permit estimation of the durability of the embedding premium and the depreciation rate of digital capability. Quasi-experimental evaluation of curricular reforms, exploiting the staggered adoption of credit-bearing digital components across institutions, would sharpen causal identification through difference-in-differences estimation. Linking student-reported capability to employer assessment and to administrative placement and wage records would resolve the appraisal-realisation gap. Multilevel modelling with institutions as level-two units and a larger institutional covariate set would identify which specific conversion resources, such as recruiter density, laboratory provision or faculty capability, generate the observed slope differentials. Finally, extension to artificial intelligence literacy as a distinct emerging capability layer is warranted, since the frameworks for teaching and assessing it are still consolidating (Hackl et al., 2025; Alekseeva et al., 2021).



## 6. Conclusion

Dual-track career preparation is defensible on evidence: across 3,085 undergraduates in 1,427 Indian university-level institutions, digital skill acquisition and traditional disciplinary depth both predicted perceived employability and career readiness in the same specification, together adding nearly thirty percentage points of explained variance to a demographically saturated baseline, with the digital track carrying the larger weight. The decisive design question is not how much digital content to add but where to place it. Propensity-matched comparison shows that identical provision delivered inside credit-bearing, assessed coursework outperforms the same provision delivered co-curricularly by roughly a third of a scale unit, which means that the prevailing institutional practice of relegating digital capability to optional space imposes a measurable and avoidable penalty.

The returns on that capability are, however, unequally exchanged. Institutional type moderates the skill-employability slope, with Institutes of National Importance converting capability into employability 43% more efficiently than state institutions, which enrol the majority of the national cohort, and digital self-efficacy moderates the skill-readiness slope by more than sixty per cent across its observed range. Two targets therefore follow with precision: the architecture of the curriculum, which must relocate digital competence into assessed disciplinary work, and the conversion infrastructure of the institution, which must be levelled if equal capability is to command equal value. Skilling policy that funds provision without governing placement and without building efficacy and conversion capacity will continue to purchase activity rather than outcomes.

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