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Bridging the Skill Gap through Start-up Driven Learning: A Study of Incubation-Based Experiential Learning in Higher Education Institutions

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Abstract
Youths are the growth engines for the developing economies like India. This study examines the role of start-up driven learning in bridging the persistent skill gap among students in higher education institutions. With increasing industry demand for job-ready graduates, traditional pedagogical approaches often fail to equip learners with practical competencies. The research focuses on incubation-based experiential learning models that integrate real-world entrepreneurial exposure into academic environments. By analysing student participation in incubation centres, start-up projects, and mentorship programs, the study evaluates the development of critical skills such as problem-solving, innovation, teamwork, and decision-making. A quantitative approach is adopted. Data were collected from 303 respondents, exceeding recommended thresholds for SEM. The findings indicate that incubation-based learning significantly enhances employability skills and entrepreneurial orientation among students. The study highlights the need for institutional support, industry collaboration, and policy-level interventions to strengthen experiential learning frameworks. It concludes that start-up driven ecosystems can serve as effective mechanisms for aligning academic outcomes with evolving industry requirements.

Keywords: *experiential learning, Start-up incubation, Skill gap, Entrepreneurship, Higher education Innovation, Industry-academia Collaboration, Incubation-based pedagogy*

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1 Introduction

The start-ups remain the top agenda for sustainable development, regional balance and employment generation. The rapidly evolving global economy, driven by technological advancements and digital transformation, has significantly altered workforce skill requirements. Higher education institutions are increasingly expected to produce graduates who are not only academically competent but also industry-ready. Studies have highlighted that conventional teaching methods often emphasize theoretical knowledge at the expense of practical application, thereby limiting students' readiness for dynamic work environments (World Economic Forum, 2020). The experiential learning has emerged as a significant pedagogical approach to address these limitations. Experiential learning emphasizes learning through action, reflection, and real-world engagement, enabling students to develop practical competencies alongside conceptual understanding (Kolb, 2015). In the Indian context, initiatives such as Startup India and Atal Innovation Mission have significantly strengthened the incubation ecosystem within higher education institutions, encouraging students to pursue innovation-driven ventures. These initiatives aim to enhance employability, promote self-employment, and contribute to economic development by nurturing entrepreneurial talent (NITI Aayog, 2021).

2. Background of the Study

A persistent mismatch exists between the competencies developed in higher education and those required by the labour market, adversely affecting graduate employability and overall economic competitiveness across both developed and developing economies (Jackson, 2016). Employers frequently highlight that many graduates lack essential workplace skills such as problem-solving, communication, and the ability to apply theoretical knowledge in practical contexts, despite substantial investments in curriculum reforms and institutional infrastructure (Mourshed et al., 2013). This situation reflects the limitations of traditional, content-driven pedagogical approaches, which prioritize knowledge transmission over skill development and fail to adequately prepare students for dynamic and complex professional environments. To address these limitations, higher education institutions have increasingly adopted experiential learning strategies aimed at enhancing practical exposure and industry relevance. Among these, university-based start-up incubators have emerged as effective platforms that provide students with opportunities to engage in innovation, idea development, prototyping, and real market interactions. These incubation environments offer authentic, hands-on learning experiences that go beyond traditional classroom simulations, enabling students to integrate technical knowledge with social and entrepreneurial competencies (Bruneel et al., 2012).

3. Significance of the Study

This study contributes significantly to the academic and practical discourse on bridging the skill gap through incubation-based experiential learning. From a theoretical perspective, it extends experiential learning theory into the domain of start-up incubation by examining how factors such as infrastructure quality, student engagement, and contextual dynamics interact to influence learning outcomes. This integration provides a more nuanced understanding of how experiential learning operates within entrepreneurial ecosystems, thereby enriching the conceptual foundation of both experiential learning and entrepreneurship education (Pittaway & Cope, 2007). This enables institutions to make informed decisions regarding resource allocation, especially in contexts with financial constraints, while optimizing the effectiveness of incubation initiatives (Fayolle, 2013). By demonstrating how incubation-based experiential learning strengthens university–industry linkages and improves graduate readiness, the research contributes to on-going policy and academic discussions on higher education transformation (Miller & Acs, 2017).

4. Problem Statement

Despite the widespread adoption of university-supported incubation programs globally, robust empirical evidence regarding their educational impact remains limited, creating uncertainty about their effectiveness in enhancing student learning outcomes (Mian et al., 2016). Although several success narratives highlight the potential of incubation ecosystems, systematic research examining how these environments contribute to the development of student capabilities is still insufficient. Significant gaps persist in understanding how infrastructural quality influences experiential learning processes, how students acquire a combination of technical, interpersonal, and entrepreneurial skills through hands-on engagement, and how such skill development translates into measurable employability outcomes. (Boh et al., 2016).

5. Objectives of Study

- To examine the influence of incubation infrastructure quality and academic–industry integration on experiential learning engagement among students
- To analyze the impact of experiential learning engagement on the development of technical skills, soft skills, and entrepreneurial mindset among students
- To evaluate the direct and indirect effects of experiential learning, skill development, and entrepreneurial mindset on innovation readiness and employability outcomes using PLS-SEM

- To assess the mediating role of experiential learning engagement in linking incubation infrastructure and academic–industry integration with students

6. Literature Review

According to Kumari (2026), the start-up driven learning has gained prominence as an innovative pedagogical approach that integrates entrepreneurial ecosystems with academic learning to enhance employability skills. Recent studies highlight that entrepreneurship education significantly strengthens learners' entrepreneurial intentions, innovation capacity, and adaptability to dynamic market conditions. This approach exposes students to real-time problem-solving environments, enabling them to develop critical thinking, risk-taking ability, and opportunity recognition skills essential for start-up ecosystems. Furthermore, the convergence of entrepreneurship with interdisciplinary domains such as STEM education enhances both technical and entrepreneurial competencies, thereby addressing industry skill mismatches (Espino et al., 2026). Such integration ensures that learners are not only theoretically sound but also practically equipped to engage in venture creation and innovation-driven economies. Consequently, start-up driven learning serves as a critical mechanism for bridging the gap between academic outcomes and industry expectations.

Business incubation has evolved as a strategic institutional mechanism that supports skill development through mentoring, networking, and access to entrepreneurial ecosystems. Contemporary research emphasizes that entrepreneurship education frameworks, when combined with incubation support, significantly enhance learners' competencies such as creativity, self-efficacy, and problem-solving abilities (European Entrepreneurship Education Research Association, 2025). Incubation centres provide experiential exposure by facilitating real venture creation, thereby strengthening practical skills and industry readiness. Moreover, structured incubation programs foster innovation ecosystems that align educational outputs with labour market demands, ensuring better employability outcomes. Empirical evidence suggests that entrepreneurship education and incubation jointly contribute to the development of entrepreneurial skills and aspirations, particularly when supported by hands-on learning environments (Xanthopoulou, 2025). Thus, incubation acts as a bridge between theoretical knowledge and real-world application, effectively reducing the prevailing skill gap.

Experiential learning has emerged as a transformative educational strategy that emphasizes learning through practice, reflection, and real-world engagement. Recent studies demonstrate that experiential learning approaches such as simulations, live projects, and mentorship play a critical role in developing entrepreneurial competencies and professional skills (Halalsheh, 2026). These methods enhance students' ability to apply theoretical concepts in practical contexts, thereby improving employability and workplace readiness. Additionally, experiential learning fosters higher levels of engagement, collaboration, and critical thinking, which are essential for addressing complex business challenges. Research further indicates that hands-on learning activities, including team-based projects and business model development, significantly strengthen students' entrepreneurial mindset and social innovation capabilities (Xanthopoulou, 2025). Consequently, experiential learning serves as a vital tool in bridging the gap between education and industry by equipping learners with both technical and soft skills required in contemporary work environments.

Pittaway & Cope (2007) contributed by extending experiential learning theory into the context of start-up incubation, offering a deeper understanding of how learning occurs within entrepreneurial ecosystems. It emphasizes the interaction between incubation infrastructure, student engagement, and contextual factors in shaping meaningful learning outcomes. By situating experiential learning within incubation environments, the study enriches the conceptual discourse on entrepreneurship education and provides a structured lens to examine how real-world exposure enhances knowledge application and skill development. This integration is particularly valuable as it moves beyond traditional classroom-based interpretations of learning and aligns theory with contemporary innovation-driven educational practices.

Some studies offer actionable insights for university leaders, incubation managers, and policymakers aiming to bridge the skill gap effectively. By identifying the key elements of infrastructure and engagement that significantly influence employability; the research supports more strategic allocation of institutional resources, particularly in resource-constrained settings. Furthermore, it reinforces the evolving role of universities as active contributors to innovation ecosystems, highlighting their responsibility to produce industry-ready graduates. Incubation-based experiential learning thus emerges as a timely and impactful approach for enhancing graduate outcomes while simultaneously strengthening university–industry collaboration and economic relevance (Miller & Acs, 2017).

7. Research Gap

From a methodological perspective, the study advances empirical research by developing and validating measurable constructs related to incubation infrastructure quality and experiential engagement, which have remained underexplored in prior literature. These constructs enable a more systematic evaluation of how incubation environments influence student learning processes and outcomes. The study provides a robust framework that can be used by future researchers to assess the effectiveness of incubation-based learning models, thereby addressing the lack of standardized measurement in this domain. Such methodological rigor strengthens the reliability and applicability of findings in understanding the role of experiential learning in higher education Despite growing attention to entrepreneurship education and incubation, important gaps remain. Most research focuses on business outcomes, like venture survival or funding, rather than the educational benefits of incubation. Few studies use integrated frameworks that combine infrastructure quality, learning processes, skill development, and employability outcomes. The influence of academic–industry integration on learning effectiveness is also underexplored, and the pathways connecting incubation experiences to employability remain unclear. This study addresses these gaps by developing and empirically testing a comprehensive model of incubation-based experiential learning, offering both theoretical insights and practical guidance for higher education leaders seeking evidence-based strategies to design and manage incubation programs effectively.

Figure 1: Conceptual Model

(Source: Author's Conceptualization)

8. Research Methodology

- **Research Design and Philosophical Approach:**

This study adopts a quantitative research design grounded in a positivist perspective, aiming to objectively examine relationships between key variables using statistical methods. A cross-sectional survey was conducted to explore links between incubation infrastructure quality, experiential learning engagement, skill development, and employability at a single point in time. This design is well suited for testing theory-driven hypotheses involving multiple interconnected constructs, particularly within a structural equation modeling framework.

- **Sampling Strategy and Data Collection:**

The study targeted students actively participating in university-affiliated incubation programs across several institutions. A purposive sampling approach selected centers operating for at least three years to ensure programs were mature enough for meaningful evaluation. Data were collected from 303 respondents, exceeding recommended thresholds for SEM. Using the 10-times rule, with no construct having more than seven incoming paths, the minimum required sample was 70. This sample size provides adequate power to detect medium-sized effects at standard significance levels.

A structured online questionnaire, distributed through institutional and incubation center channels, used validated scales adapted from prior studies. Responses were recorded on seven-point Likert scales, from strongly disagree to strongly agree. A pilot study with 35 participants ensured item clarity, identified ambiguities, and provided preliminary reliability estimates.

- **Data Analysis Technique**

Data analysis was carried out using SmartPLS 4.0 with partial least squares structural equation modeling (PLS-SEM). PLS-SEM was chosen over covariance-based SEM because it is well suited for exploratory studies, handles complex models with multiple constructs, requires fewer assumptions about data distribution, and performs reliably with moderate sample sizes. This aligns with the study's focus on prediction and theory development rather than strict hypothesis testing.

The analysis followed a two-step process. First, the measurement model was evaluated to ensure reliability and validity. Reliability was checked using Cronbach's alpha, composite reliability, and rho_A, with values above 0.70 considered acceptable. Convergent validity was assessed through factor loadings and average variance extracted (AVE), while discriminant validity was confirmed using the Fornell–Larcker criterion and the heterotrait–monotrait (HTMT) ratio.

In the second step, the structural model was tested to examine hypothesized relationships among constructs. Path coefficients, R^2, effect sizes (f^2), and predictive relevance (Q^2) were estimated, with bootstrapping using 5,000 resamples applied to assess stability and significance. Relationships were deemed significant at the 5 percent level, and effect sizes were interpreted using Cohen's (1988) guidelines.

9. Results and Discussion

- **Measurement Model Assessment**

Before testing the structural relationships, the measurement model was examined to ensure that all constructs were measured in a reliable and valid way (Hair et al., 2017).

Table 1: Reliability and Validity Assessment

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AII	0.892	0.893	0.925	0.755
ELE	0.903	0.906	0.932	0.775
EMD	0.828	0.84	0.885	0.659
IIQ	0.855	0.86	0.901	0.696
IRE	0.813	0.82	0.877	0.641
SSE	0.881	0.892	0.926	0.808
TSD	0.93	0.933	0.95	0.827

Source: Primary Data Analysis

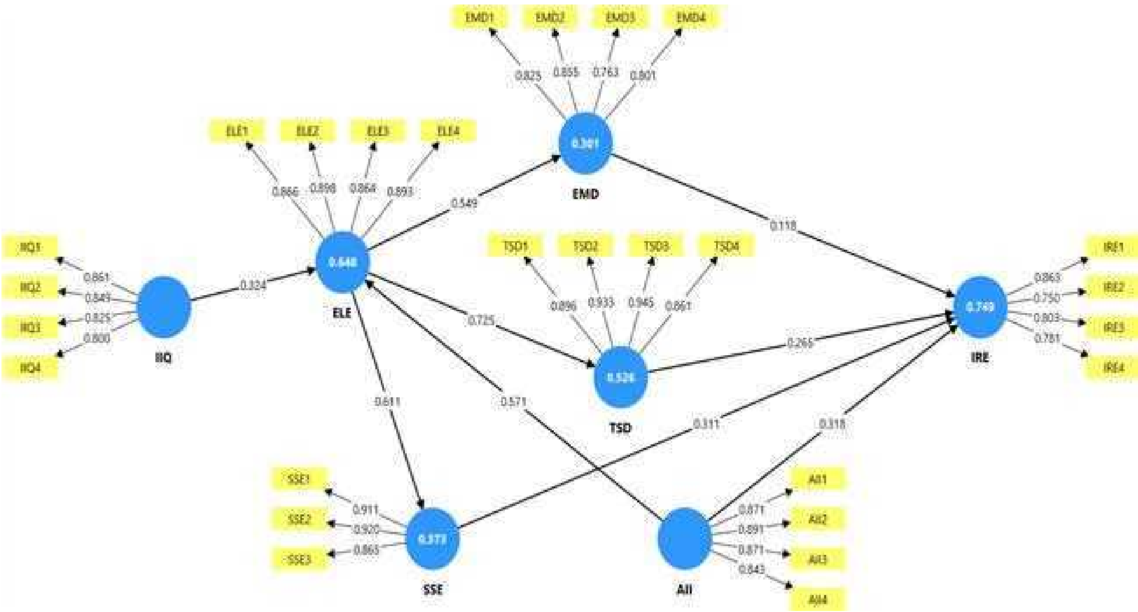
Table 1 presents a summary of the results for reliability and convergent validity across the seven constructs included in the proposed model.

The measurement results show strong evidence of reliability and validity across all constructs. Cronbach's alpha values range from 0.813 to 0.930, well above the 0.70 threshold indicating high internal consistency, with each construct's items reliably capturing the same underlying concept.

Composite reliability further confirms this, with rock values between 0.877 and 0.950 and rhea values from 0.820 to 0.933, all exceeding 0.70. These results demonstrate that the indicators consistently represent their respective latent constructs, which is particularly important in PLS-SEM where composite reliability offers a more precise measure of construct quality.

Convergent validity is also strong, with Average Variance Extracted (AVE) values ranging from 0.641 to 0.827, above the 0.50 benchmark showing that more than half of the variance in each construct's indicators is explained by the latent variable.

Figure 2: Measurement Model



Source: SmartPLS4 Output of Data Analysis

Discriminant validity, assessed using the Fornell–Larcker criterion, is satisfactory, as the square root of AVE for each construct exceeds its correlations with all others. Although IRE shows moderate correlations with AII (0.789) and TSD (0.755), these remain below the AVE square root, indicating only minor overlap (Table 2).

Table 2: Discriminant Validity – Fornell-Larcker Criterion

	AII	ELE	EMD	IIQ	IRE	SSE	TSD
AII	0.869						
ELE	0.761	0.880					
EMD	0.541	0.549	0.812				
IIQ	0.587	0.659	0.514	0.834			
IRE	0.789	0.667	0.560	0.558	0.800		
SSE	0.687	0.611	0.434	0.429	0.748	0.899	
TSD	0.731	0.725	0.510	0.628	0.755	0.634	0.909

Source: Primary Data Analysis

The HTMT matrix was used to assess discriminant validity by examining the heterograft–monorail ratios between all pairs of constructs (Table 3). All HTMT values fall between 0.481 and 0.817, which is well below the conservative threshold of 0.85. This indicates that the constructs are empirically distinct. The highest HTMT value, observed between SSE and IRE (0.817), reflects a moderately strong relationship, but it remains within acceptable limits. This suggests that while the two constructs are related, they capture different underlying concepts.

Table 3: Discriminant Validity – HTMT Matrix

	AII	ELE	EMD	IIQ	IRE	SSE	TSD
AII							
ELE	0.844						
EMD	0.618	0.621					
IIQ	0.667	0.743	0.599				
IRE	0.721	0.768	0.682	0.666			
SSE	0.768	0.678	0.498	0.481	0.817		
TSD	0.802	0.786	0.573	0.698	0.803	0.693	

Source: Primary Data Analysis

- **Structural Model Assessment**

The structural model was evaluated using a bootstrapping procedure with 5,000 resamples to test the proposed hypotheses. Table 4 presents the estimated path coefficients, along with their corresponding t-values, p-values, and levels of statistical significance for all direct relationships in the model.

The structural model results show that all proposed relationships are positive and statistically significant, offering strong empirical support for the research framework. These findings confirm that the model is robust and that the theoretical assumptions guiding the study hold up well in practice.

Table 4: Structural Model-Path Coefficients for Hypotheses Testing

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decision
AII -> ELE	0.571	0.573	0.054	10.567	0.000	Supported
AII -> IRE	0.318	0.319	0.053	5.948	0.000	Supported
ELE -> EMD	0.549	0.552	0.051	10.699	0.000	Supported
ELE -> SSE	0.611	0.612	0.036	16.816	0.000	Supported
ELE -> TSD	0.725	0.725	0.028	25.442	0.000	Supported
EMD -> IRE	0.118	0.12	0.04	2.98	0.003	Supported
IIQ -> ELE	0.324	0.322	0.06	5.424	0.000	Supported
SSE -> IRE	0.311	0.311	0.043	7.218	0.000	Supported
TSD -> IRE	0.265	0.263	0.049	5.465	0.000	Supported

Source: Primary Data Analysis

The path from AII to ELE is particularly strong ($\beta = 0.571$, $p < 0.001$), indicating that AII plays a major role in strengthening ELE. AII also has a significant positive effect on IRE ($\beta = 0.318$, $p < 0.001$), suggesting that improvements in AII are directly associated with higher levels of IRE. In a similar way, IIQ shows a significant positive relationship with ELE ($\beta = 0.324$, $p < 0.001$), highlighting the importance of IIQ in supporting experiential learning engagement.
ELE, in turn, has a strong positive influence on EMD ($\beta = 0.549$, $p < 0.001$), SSE ($\beta = 0.611$, $p < 0.001$), and TSD ($\beta = 0.725$, $p < 0.001$). Among these relationships, the effect of ELE on TSD is the strongest, underscoring ELE's central role within the model. EMD also shows a smaller but still meaningful positive effect on IRE ($\beta = 0.118$, $p = 0.003$), indicating that it contributes to IRE even if its influence is more modest. Both SSE ($\beta = 0.311$, $p < 0.001$) and TSD ($\beta = 0.265$, $p < 0.001$) display moderate and statistically significant effects on IRE, confirming their importance as key predictors. Taken together, these results point to ELE as a pivotal mediating factor that strongly shapes several internal outcomes, which then go on to enhance IRE. The consistent significance of

these paths suggests that the proposed structural model is well supported and provides a clear and effective explanation of the relationships among the study's core constructs. The results show that the model explains a large share of the variance in IRE, with an R^2 value of 62.3% (Table 5). This suggests that the combined influence of AII, EMD, SSE, and TSD provides a strong prediction of IRE. ELE is also well explained by the model, with 45% of its variance accounted for by AII and IIQ, further underscoring the strength of the proposed relationships.

Table 5: Model Predictive Accuracy and Effect Sizes

Endogenous Construct	R^2	R^2 Adjusted
ELE	0.450	0.448
TSD	0.475	0.473
SSE	0.419	0.417
EMD	0.382	0.380
IRE	0.623	0.619

Source: Primary Data Analysis

The explained variance for TSD (47.5 %), SSE (41.9 %), and EMD (38.2 %) falls within a moderate range, confirming that ELE acts as a key driver for these constructs. Taken together, these R^2 values indicate that the research model has well to substantial predictive power and offers strong support for the underlying theoretical framework.

- **Model Fit Assessment**

The model fit was evaluated using several goodness-of-fit indicators commonly recommended for PLS-SEM. The standardized root mean square residual (SRMR) for the estimated model was 0.098, which is within the acceptable threshold of 0.10 and suggests an adequate fit between the observed data and the model's implied correlations. The saturated model showed an even lower SRMR value of 0.067, indicating a good representation of the underlying data structure (Table 6).

Additional discrepancy measures, including the squared Euclidean distance (d_ULS = 3.604) and the geodesic distance (d_G = 0.835), were higher for the estimated model than for the saturated model (d_ULS = 1.682; d_G = 0.716), as expected. Importantly, these values do not point to any serious model misspecification, suggesting that the model fits the data reasonably well.

Table 6: Model Fit

	Saturated model	Estimated model
SRMR	0.067	0.098
d_ULS	1.682	3.604
d_G	0.716	0.835
Chi-square	1295.928	1404.96
NFI	0.78	0.794

Source: Primary Data Analysis

The chi-square value rose from 1295.928 in the saturated model to 1404.960 in the estimated model, which is normal in PLS-SEM and not considered a strict measure due to its sensitivity to sample size. The normed fit index (NFI) for the estimated model was 0.794, indicating an acceptable level of model fit within variance-based structural equation modelling. Overall, these results suggest the model has satisfactory global fit, making it suitable for hypothesis testing and further structural analysis.

10. Findings of Study

- The study reveals that incubation-based experiential learning plays a significant role in bridging the skill gap among students in higher education institutions. It was found that students who actively participate in start-up incubation activities demonstrate higher levels of engagement in experiential learning processes compared to those exposed only to traditional classroom methods. The availability of quality incubation infrastructure including mentoring support, access to resources, networking opportunities, and collaborative workspaces positively influences student involvement in practical learning activities.

- The findings further indicate that experiential learning within incubation environments contributes substantially to the development of both technical and soft skills. Students involved in start-up activities exhibit improved domain-specific competencies such as business planning, market analysis, and problem-solving, alongside enhanced interpersonal skills including communication, teamwork, leadership, and adaptability.
- The study establishes that academic–industry integration acts as a critical enabler in strengthening experiential learning outcomes. Institutions with strong linkages to industry partners provide students with more authentic exposure to market realities, thereby deepening their learning experience. The results also suggest that experiential learning serves as a mediating factor between incubation infrastructure and employability outcomes, indicating that the mere presence of infrastructure is insufficient without active student engagement.

11. Conclusion

This study provides strong evidence that incubation-based experiential learning is an effective way to close the persistent skills gap between higher education and industry. The validated framework shows clear pathways from high-quality infrastructure to experiential engagement, leading to multidimensional skill development and enhanced employability. Well-designed incubation programs foster meaningful engagement that simultaneously builds technical skills, soft skills, and an entrepreneurial mind-set together driving industry readiness. The moderating role of academic–industry integration emphasizes the value of partnerships that span institutional boundaries in amplifying learning outcomes.

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