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Research paper

From Campus to Career: How Emerging Technology Influences Placement Outcomes through The Student Preparedness and Confidence

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Abstract

Purpose: The study aims to investigate how emerging technology is vital for gaining a competitive advantage in student placement outcomes in the universities of Tamil Nadu.
Approach: The conceptual framework of the research is based on various technological factors adapted from human capital theory and social cognitive theory, which contribute to the outcome. The relationship examines the mediating effects of student preparedness and confidence within the model. A sample of 402 students from different private universities in Tamil Nadu was surveyed using a pretested questionnaire. The empirical validation of the framework and analysis was done using smart PLS structural equation modelling. The research also investigates how age and gender act as moderators to better understand the various impacts of technology-enhanced learning.
Result: Student preparedness strongly predicts student confidence, boosting placement success. These findings offer theoretically and practically valuable insights that can guide university administrators, policymakers, and corporate recruiters in enhancing graduate employability in an increasingly digital educational landscape.

Keywords: *Emerging Technology; Student Preparedness; Student Confidence; Placement Outcome; Higher Education Employability.*

1. Introduction

Higher education and labour markets have been transformed by the fourth industrial revolution; this is a fast-moving adoption of artificial intelligence, analytics, cloud technologies and online learning platforms (Schwab, 2016). Gradually universities are adopting these technologies in order to modernize the teaching process and enhance the labour-market readiness of the students (Agarwal & Chakrabarti, 2020). In the developing world like India, the ability to navigate through technology-enabled learning conditions has become a primary precursor of employability and future income, which is consistent with the human capital investment theme (Ghosh, 2021; Becker, 1993). Even with the high level of exposure to technology, a number of graduates remain unable to transform the digital learning experiences into employment-related competencies. The barriers to structure include the imbalance of digital access, insufficient customization of training, and the unequal distribution of faculty and institutional resources, which influence student accomplishments in the translation of education into labour-market results (Sarma & Pattanayak, 2022). Further, psychological skills like preparedness and self-confidence will also affect these investments to be realised, which resonates with the Social Cognitive Theory (Bandura, 1997) and the debates of behavioural capability and job-search effectiveness in employability economics. Age and gender are some of the demographic variables that influence technology adoption and skill formation patterns, which increase differentiated returns to labour in the labour-market (Chin and Lee, 2021). This study addressed the problem by examining the following research questions:

- RQ1: How does emerging technology influence the outcome of student placement in universities?
- RQ2: Do student preparedness and student confidence mediate the relationship between emerging technologies and placement outcome, and how do these relationships differ across varying age groups and genders?

To investigate these questions, the study draws from two foundational theories. Human Capital Theory (Becker, 1993) posits that investments in education and skill development directly enhance an individual's productivity and employment opportunities. Complementing this, Social Cognitive Theory (Bandura, 1997) emphasizes the role of self-efficacy, motivation, and learning through social interaction in determining behavior and outcomes. These frameworks, together, provide a multidimensional lens to assess how technological exposure translates into employability through internal mediators, such as preparedness and confidence.

1.1. Research objectives

- To investigate the immediate role of the new technologies in the placement outcome of students.
- To examine the mediating variables of student preparedness and confidence in the transformation of technological exposure to employability.
- To investigate the impact of demographic variables, age, and gender, on the usage of technology among students and their success in placements.

The research has added value to the existing literature on the topic of employability and digital learning through the clarification of the nexus of interaction between new technologies, psychological preparedness, and labour-market outcomes. It demonstrates the frequently neglected mediating positions of student preparedness and student confidence and expands on conventional models of placement which only consider academic contributions in a thin manner (Jackson & Wilton, 2017). The study has also included an essential distributional view that is useful in the field of educational and labour-market economics, with differences in age and gender, as individual factors that determine the digital engagement and employability outcomes. The study used a quantitative design to investigate these relationships with the students of the university in Tamil Nadu. The hypothesis that the emerging technologies have a sequential effect on the placement outcomes through the mediating role of preparedness and confidence was tested by implementing a serial mediation model (Kumar and Chandrasekaran, 2021). The findings indicate that each of the paths is positive and significant, which highlights that the technological exposure should be supported by the internal behavioural factors to increase the performance of students in the placement and readiness to the labour market. To support the study with the broader economics and educational policy perspectives, the results also highlight the importance of skill development through technology as a contributor to the human capital formation which is a major theme in labor economics. The more the emerging technologies equip students with greater preparedness and confidence, the more the competence of graduates is raised in terms of employability, and thus the more the base of job-ready human capital is provided to the labor market. This is in line with the framework of the human capital theory, that suggests that acting on specific investments in learning infrastructure and digital capabilities results in quantifiable economic output on individual and institutional scales. Policy wise, the findings affirm the importance of universities and colleges to focus on digital learning environments as stipulated in the new Indian policies on education and international employability. It is through this alignment that the universities are not only able to improve the performance of the students but also meet the economical macro-level goals that are associated with the development of the workforce, increased productivity, and competitiveness, which are important concerns to Accounting and Economics Studies.

2. Theoretical Framework

2.1. Emerging technology and student development

Emerging technology is pivotal in enhancing student development in higher education, particularly in improving career readiness and access to placement opportunities. The Technology Acceptance Model, provides a foundation for understanding how students' perceptions of the usefulness and ease of use of technology influence their intention to adopt digital tools for employability enhancement. These include AI-powered résumé builders, virtual interview simulators, online certification platforms, and adaptive e-learning modules (Venkatesh & Bala, 2008). In higher education institutions, such technologies are increasingly employed to bridge the gap between academic instruction and industry expectations by offering scalable, personalized, and interactive learning experiences (Al-Emran et al., 2018).

When students perceive these tools as effective in enhancing their employment prospects, they are more inclined to integrate them into their career preparation strategies (Teo, 2011). Moreover, digital exposure enhances cognitive engagement, practical skill application, and behavioral adaptability, which are critical for placement readiness (Marginson,2017). Consequently, emerging technologies catalyze placement outcomes by making students more technologically fluent, confident, and adaptable to real-world challenges (Alshurideh et al., 2021).

2.2. Placement outcomes and student's educational experience

Capital Human Theory (Becker, 1964) designed to reveal the functional relationship and effectiveness of a student's educational journey with technology and outcome. The theory offered by Becker (1964) provides a robust framework to explain this linkage, asserting that educational, training, and skill acquisition investments enhance productivity and career success. Students pursuing additional qualifications, digital certifications, and professional experiences augment their market value and employability (Mishra, 2020). This aligns with institutional efforts to build employability through placement cells, career counseling, and AI-based job-matching platforms, especially within Indian universities (OECD, 2020).

Furthermore, placement outcomes serve as feedback loops that reinforce the perceived value of educational investments (Tomlinson, 2017). Institutions that strategically incorporate emerging technologies into teaching and career services contribute to academic success and meaningful employment opportunities, thereby validating the cyclical nature of human capital development (Knight & Yorke, 2004). In this context, placement outcomes are not incidental but are shaped by a systematic interplay of institutional resources, student efforts, and technological facilitation.

2.3. Social cognitive theory and the mediating role of student preparedness and confidence

Student preparedness including academic readiness, communication skills, and hands-on experiences, is a critical enabler of successful career transitions. Drawing on Social Cognitive Theory (SCT) (Bandura, 1986), preparedness contributes to the development of self-efficacy, which in turn fosters student confidence. (Talsma et al., 2018) states the mastery experiences gained from internships, simulations, mock interviews, and co-curricular engagements, students develop a belief in their ability to perform well in placement settings (Zimmerman, 2000). However confidence stated in the theoretical framework is not merely a static personality trait but is dynamically shaped through continual exposure to performance-based tasks in authentic settings (Bandura, 2001). Technologies such as virtual reality assessments, real-time feedback systems, and AI-driven career platforms support students by offering structured, iterative, and personalized learning experiences (Schunk & DiBenedetto, 2020). In placement-driven institutions, especially in India, student preparedness and confidence act as essential mediators that translate digital access and academic resources into enhanced employability (Lent et al., 1994).

3. Literature Review

3.1. Emerging technologies and placement outcomes

Integrating emerging technologies into higher education has received growing attention in recent years, particularly its impact on students' employability and career prospects (Escueta et al., 2017). These technologies ranging from learning management systems and AI-based learning analytics to simulation tools and blockchain credentials, are transforming both instructional delivery and student experience (Zou et al., 2025). As the job market becomes increasingly digitized, higher education institutions are tasked with aligning their pedagogy to meet industry expectations by cultivating digital literacy and 21st-century competencies (Timotheou et al., 2022). Evidence shows that educational technologies can serve as catalysts for enhancing students' critical thinking, communication, and adaptability key traits employers seek in a tech-driven job market (Alshurideh et al., 2021). For example, AI-powered résumé tools, virtual job simulations, and real-time feedback platforms enable students to practice in realistic environments, boosting their competence and confidence (Escueta et al., 2017). Conversely, the pressure to improve placement outcomes has also driven institutions to adopt more emerging technologies (Sharma, R., & Yadav, A., 2020). Fields such as data science, cybersecurity, AI, and blockchain are increasingly embedded in curricula to match labor market trends (Kumar & Sharma, 2022). Studies show that students who graduate with specialized digital competencies tend to perform better in placement drives (Patel et al., 2021). Furthermore, universities that develop strong industry linkages, offer interdisciplinary training, and provide experiential learning opportunities demonstrate higher placement success (Usher & Pajares, 2008). However, challenges such as digital access inequality and the readiness of faculty to integrate new tools remain critical obstacles (OECD, 2020). Addressing these gaps is essential to create equitable pathways for all students to benefit from technology-enhanced education and employment outcomes (Sarma & Pattanayak, 2022). These tools prepare students to meet evolving employer expectations and increase their likelihood of securing quality placements. Student placement is a crucial aspect of higher education, offering practical experience that complements theoretical learning (Kalyani, 2024) . One increasingly influential factor in placement readiness is the use of emerging technologies. To understand how these technologies affect placement outcomes, it is essential to examine the concepts of student preparedness, confidence, and the role of technology in shaping employability outcomes (Tarhini et al., 2017). Several studies have supported the bidirectional relationship between technology and placement outcomes. As emerging technologies enhance student capabilities, they simultaneously raise employers' expectations, reinforcing the continuous skill advancement cycle (Zou et al., 2025). This dynamic relationship suggests that technologies influence placement outcomes, and the demand for better placement results also accelerates technological adoption in higher education.
Hypothesis 1: Emerging technologies towards placement outcome are positively related to placement outcome towards emerging technologies.

3.2. Student preparedness as a mediator between emerging technology and placement outcomes

Student preparedness is the extent to which students are equipped with relevant academic knowledge, soft skills, and professional experience to participate in placements effectively (Jackson, 2016). Beyond theoretical knowledge, students are now expected to master critical skills such as adaptability, problem-solving, and communication, often developed through technological tools like virtual labs, AI-driven simulations, and digital internships (Sharma, R., Yadav, A.,2020). Preparedness in the era of hybrid placements also involves digital flexibility and the ability to engage in remote work environments, emphasizing the need for resilience and continuous learning. Both cognitively and behaviorally, well-prepared students are more likely to translate their education into real-world success during placements (Jackson, 2016).
Hypothesis 2: The relationship between emerging technologies and placement outcome mediated by student preparedness.
Hypothesis 2a: Emerging technologies positively related to placement outcome
Hypothesis 2b: Student preparedness positively related to placement outcome.

3.3. Student confidence as a mediator between emerging technology and placement outcomes

Student confidence significantly affects how learners engage with placement opportunities. Confidence, closely tied to Bandura's (1997) concept of self-efficacy, influences not only students' willingness to pursue opportunities but also their ability to persist in challenging environments. Students who develop confidence through digital tools such as interactive learning platforms, self-assessment modules, and peer feedback systems are likelier to perform effectively during interviews and on the job (Fratiwi et al., 2022). Technological learning environments that allow for safe practice and iterative feedback foster a strong sense of competence, further enhancing student confidence. Confidence also affects interpersonal dynamics in placements, such as communication with supervisors and collaboration with team members.
Hypothesis 3: The relationship between emerging technologies and placement outcome mediated by student confidence.
Hypothesis 2a: Emerging technologies positively related to student confidence
Hypothesis 2b: Student confidence positively related to placement outcome
The digital transformation of higher education has been extensive and measurable over the past few decades, highlighting the importance of understanding how technology affects the relationship between student preparedness and confidence.
Hypothesis 4: The relationship between emerging technologies towards placement outcome and placement outcome towards emerging technologies is sequentially mediated by student preparedness and student confidence.

3.4. Conceptual model

The literature collectively supports the proposition that student preparedness and confidence are dual mediators in the relationship between emerging technologies and placement outcomes (Marginson, 2017). As supported by both theoretical and empirical studies, these mediators are also interrelated, suggesting a mutual reinforcement wherein higher preparedness fosters greater confidence and vice versa (Talsma et al., 2018). This framework underscores a holistic approach to understanding how technology, psychology, and institutional factors interact to determine employability.
Overall, integrating TAM, Human Capital Theory, and Social Cognitive Theory provides a comprehensive framework to understand how technological exposure, student agency, and institutional investment converge to shape placement outcomes.

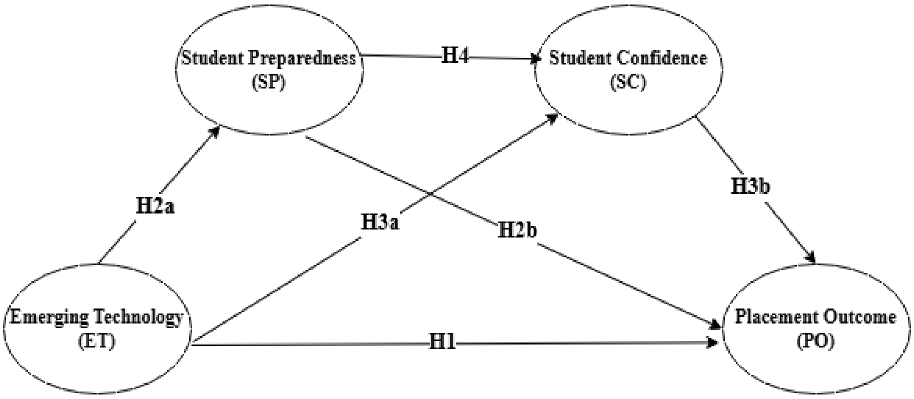

Fig. 1: Serial Mediation Model.

The hypotheses for this study were formulated based on the serial mediation effects proposed in the conceptual model presented in Figure 1.
H_1 = Emerging Technology□ Placement Outcomes
H2 = Emerging Technology □□Student Preparedness □ Placement Outcomes
H3 = Emerging Technology□□Student Confidence□ Placement Outcomes
H4 = Emerging Technology□ Student Preparedness □ Student Confidence□□Placement Outcomes

4. Methodology

4.1. Sample and procedure

Final-year students of major universities in the Tamil Nadu state which is identified in terms of high-quality academic infrastructure as stated in the AICTE (2025) and NIRF (2025) rankings, became the subject of a cross-sectional-based field survey. (This is a direct reply to the request of the reviewer that concise and high-level context, rather than excessive narrative These universities were a combination of the public, private, and Tier-1 autonomous universities to facilitate the coverage of the major types of higher education institutions in the state. The final-year students were chosen strategically since they are the group moving to the labor market, and hence a suitable group to study the impact of emerging technologies on the readiness and placement outcomes. The choice of Tamil Nadu as a state is due to the fact that it is one of the leading Indian states in terms of institutional quality, digital preparedness, and industry connectivity, which makes it a feasible setting to research employability.
The data collection process was structured in terms of university placement offices with the help of two data collection means: (a) email invitations to eligible students (N = 950), (b) paper-based questionnaires, which were distributed in the central campuses. The regular confidentiality and voluntary participation procedures were adhered to (Mishra, 2020). Students who took part in the qualitative pilot were sidelined in order to prevent bias.
In both modes 458 responses were obtained (48% response rate). The screened survey was limited to 402 valid surveys. The last sample was a total of 230 males (57.21) and 172 females (42.79%). The mean age was 22.6 years (SD = 1.4). Most of them (76.12%) were 23-26 years old and 23.88% were 20-23 years old. The number of students who were academically undergraduates and postgraduates was 250 (62.19) and 152 (37.81), respectively. These demographics correspond to previous placement-oriented research (Patra and Sharma, 2022)of the final 402 participants; 230 were male (57.21%), and 172 were female (42.79%). The mean age of the sample was 22.6 years (SD = 1.4). Most respondents (76.12%) were in the 23–26 age group, while the remaining (23.88%) were aged 20–23. Regarding academic level, 250 students (62.19%) were pursuing undergraduate programs, and 152 (37.81%) were postgraduates. These demographics align with prior Indian university student placement studies (Patra & Sharma, 2022), reinforcing the representativeness and appropriateness of the sample.
To confirm boundaries of sampling and enhance methodological transparency, it is worthwhile to mention that the research was restricted to big universities in Tamil Nadu. Even though the sample represents all three categories of institutions (public, private, and Tier-1 autonomous institution) and increases institutional coverage, the results might not be entirely applicable to universities in other states of India with various degrees of digital infrastructure, academic investment, and employability ecosystems. Areas with different economic statuses or access to technology might have different rates of student preparedness, confidence and placement levels. Equally, other institutions, such as Tier-2 and Tier-3, and rural universities, might have their own problem with technology adoption different than the fairly advanced higher education set-up in Tamil Nadu. Representative of these differences must be considered during the interpretation of the findings and future research can be improved with the help of the comparative sampling of the various states or types of institutions to enhance generalizability.

4.2. Measures

All variables were measured using validated Likert-type instruments on a 5-point scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Where appropriate, reverse-coded items were incorporated to reduce response biases (Podsakoff et al., 2003). Items were pilot-tested for reliability and clarity with a smaller sample (n = 35) prior to final survey distribution.

- Emerging Technologies (8 items): Based on frameworks by (Aithal & Aithal (2016), this scale assessed students' exposure to and perceptions of AI, automation, and other advanced technologies influencing labor markets. Items captured perceived preparedness, relevance, and adaptability to technology-driven job environments (Prytkova et al. 2024).
- Placement Outcomes (7 items): Drawing from (Rothwell & Arnold, 2007), this scale measured students' perceived employability, placement optimism, and readiness to enter the job market. Items reflected confidence in job opportunities, industry alignment, and placement support systems (Tomlinson, 2012).

- Student Preparedness (6 items): Adapted from (Finch et al. 2013), this scale evaluated students' self-perceptions regarding job readiness, technical competencies, and their ability to apply academic knowledge to professional contexts. Emphasis was placed on both traditional and digital skill readiness.
- Student Confidence (5 items): Developed using Bandura's (2006) academic self-efficacy scale, this measure focused on students' confidence in handling job-related tasks, adapting to work environments, and performing well in interviews or internships. This scale has been widely applied in career transition research (Fratiwi et al., 2022).

4.3. Demographic summary

The demographic composition of the sample is detailed below:

Table 1: Demographic Profile of Respondents (N = 402)

Variables	Categories	Frequency	Percentage (%)
Gender	Male	230	57.21
	Female	172	42.79
Age	20-23	96	23.88
	23-26	306	76.12
Educational Status	UG	250	62.19
	PG	152	37.81

Source: Author.

As depicted in Table 1, the demographic profile of respondents regarding educational status, a larger portion of the participants were pursuing undergraduate degrees (250 or 62.19%), with the remaining 152 (37.81%) enrolled in postgraduate programs. These demographic details highlight that the study sample predominantly comprised senior undergraduate and postgraduate students, an appropriate cohort given their proximity to graduation and relevance to placement-related inquiries. Data were collected through a structured questionnaire divided into two sections: the first measured variables related to emerging technology, preparedness, confidence, and placement outcomes; the second gathered demographic information. All items were rated on a five-point Likert scale, ensuring consistency and ease of interpretation.

5. Analysis and Results

Data analysis was conducted using Smart PLS 4 software, which employs the partial least squares approach for structural equation modeling. We opted for the PLS method instead of traditional structural equation modeling, which relies on covariance metrics, because PLS emphasizes maximizing the variance explained by independent variables. This approach is advantageous due to its minimal sample size requirements, while still providing reliable results for measurement and structural models. Therefore, PLS is well-suited to achieve the research goals of this study (J. Hair & Alamer, 2022). This method is frequently utilized by researchers in studies exploring students' perspectives on emerging technologies.

5.1 Measurement model

Table 2: Factor Loadings of the Measurement Items

Items		Factor loadings	Cronbach's alpha	CR	(AVE)
	ET1	0.737			
	ET2	0.763			
	ET3	0.675			
	ET4	0.721			
	ET5	0.694	0.839	0.842	0.509
Emerging Technology	ET6	0.725			
	ET7	0.676			
	PO1	0.901			
Placement Outcome	PO2	0.948	0.895	0.897	0.828
	PO3	0.880			
	SC1	0.690			
	SC2	0.700			
	SC3	0.790			
	SC4	0.842			
Student Confidence	SC5	0.865	0.875	0.877	0.618
	SC6	0.813			
	SP1	0.769			
	SP2	0.802			
	SP3	0.823			
Student Preparedness	SP4	0.888	0.887	0.896	0.688
	SP5	0.861			

Source: Author.

The measurement model illustrated in Table 2 was established to evaluate the reliability and validity of all four constructs in this study: Emerging Technology, Student Preparedness, Student Confidence, and Placement Outcome. Regarding the factor loadings, all exceeded the recommended threshold of 0.60, confirming acceptable indicator reliability (Hair et al., 2019). The construct reliability was assessed using Cronbach's alpha and composite reliability (CR). The Cronbach's alpha values ranged from 0.839 to 0.895, and the CR values ranged from 0.842 to 0.897, indicating high internal consistency across all constructs (Henseler et al., 2015).

The average variance extracted (AVE) was calculated to evaluate convergent validity, with all constructs achieving values above the minimum acceptable threshold of 0.50 (Fornell & Larcker, 1981). Specifically, the AVE for Emerging Technology was 0.509, for Student Confidence was 0.618, for Student Preparedness was 0.688, and for Placement Outcome was 0.828, supporting convergent validity.

Table 3: Discriminant Validity (HTMT Ratio)

Construct	(ET)	(PO)	(SC)	(SP)
Emerging Technology(ET)				
Placement Outcome(PO)	0.560			
Student Confidence(SC)	0.595	0.475		
Student Preparedness(SP)	0.500	0.392	0.716	

Source: Author.

The structural model was evaluated for discriminant validity from Table 3, depicting the strength of hypothesized relationships among the constructs. Discriminant validity was assessed using the Heterotrait–Monotrait (HTMT) ratio, as shown in Table 3. All HTMT values ranged from 0.392 to 0.716, well below the conservative threshold of 0.85 (Hair et al., 2019), confirming that the constructs are distinct and non-redundant.

Table 4: Model Goodness-of-Fit Summary

Goodness-of-Fit Index	Value	Recommended Threshold	Status
Chi-Square/df (CMIN/DF)	2.346	< 3.00	Acceptable
Root Mean Square Error of Approximation (RMSEA)	0.062	< 0.08	Good Fit
Comparative Fit Index (CFI)	0.952	> 0.90	Good Fit
Tucker–Lewis Index (TLI)	0.937	> 0.90	Good Fit
Standardized Root Mean Square Residual (SRMR)	0.052	< 0.08	Good Fit

Source: Author.

Based on multiple indices in Table 4, the model fits the observed data well. The chi-square/df ratio of 2.345 falls within the acceptable limit, suggesting a reasonably fitting model (Hair et al., 2019). The RMSEA and SRMR, both below 0.08, support the appropriateness of model approximation. CFI and TLI values exceeding 0.90 indicate strong comparative and incremental fit. Hence, the model adequately represents the observed data and is suitable for testing the proposed structural relationships.

Table 5: Path Estimates

Structural Relationship	β	T statistics	P values	Result
Emerging Technology -> Placement Outcome	0.360	7.840	0.000	Supported
Emerging Technology -> Student Confidence	0.287	7.573	0.000	Supported
Emerging Technology -> Student Preparedness	0.433	8.864	0.000	Supported
Student Confidence -> Placement Outcome	0.191	3.374	0.001	Supported
Student Preparedness -> Placement Outcome	0.177	3.593	0.000	Supported
Student Preparedness -> Student Confidence	0.537	15.493	0.000	Supported

Source: Author.

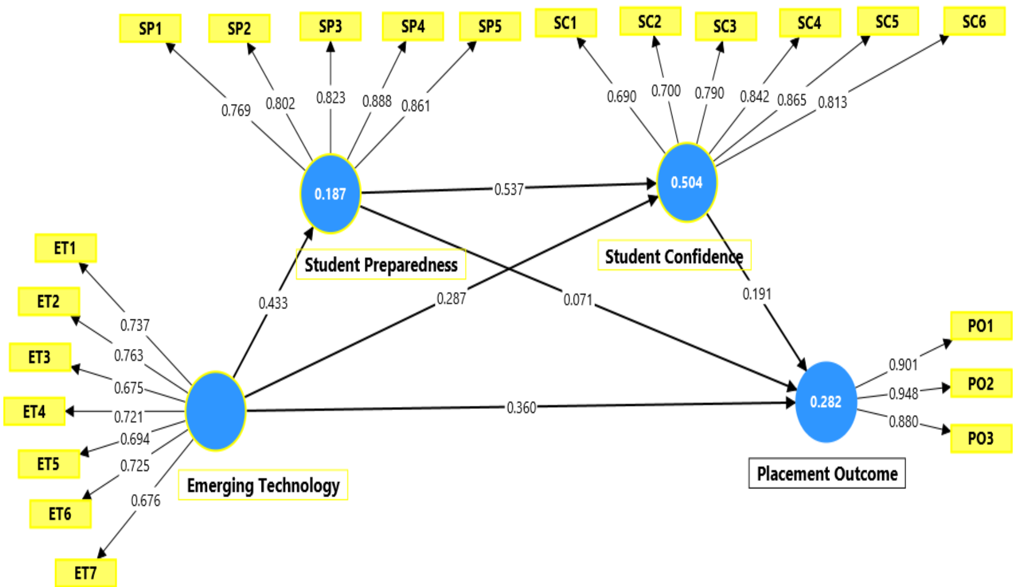

Fig. 2: Results of the Structural Equation Model Using PLS-SEM.

Path analysis results presented in Table 5 and Figure 2 demonstrate strong support for all hypothesized relationships. Emerging Technology exhibited a significant positive effect on Placement Outcome (β = 0.360, t = 7.840, p < 0.001), Student Confidence (β = 0.287, t = 7.573, p < 0.001), and Student Preparedness (β = 0.433, t = 8.864, p < 0.001), suggesting that students' exposure to and engagement with emerging technologies substantially enhances both their readiness and self-assurance regarding employability. Student Confidence significantly influenced Placement Outcome (β = 0.191, t = 3.374, p = 0.001), while Student Preparedness also had a positive impact on Placement Outcome (β = 0.177, t = 3.593, p < 0.001), confirming their mediating roles. Additionally, Student Preparedness was a strong predictor of Student Confidence (β = 0.537, t = 15.493, p < 0.001), indicating that better-prepared students tend to exhibit greater confidence when approaching placement opportunities. Collectively, these results validate the conceptual model and highlight emerging technology's central role in shaping student perceptions and placement outcomes.

Table 6: Mediation Analysis

Hypotheses	Structural relationship	β	T statistics	P values	Result
Direct Effect					
H1	Emerging Technology -> Placement Outcome	0.360	7.840	0.000	Supported
H2a	Emerging Technology -> Student Preparedness	0.433	8.864	0.000	Supported
H2b	Student Preparedness -> Placement Outcome	0.177	3.593	0.000	Supported
H3a	Emerging Technology -> Student Confidence	0.287	7.573	0.000	Supported
H3b	Student Confidence -> Placement Outcome	0.191	3.374	0.001	Supported
Indirect effect					
H2	Emerging Technology -> Student Preparedness -> Placement Outcome	0.031	3.002	0.000	Supported
H3	Emerging Technology -> Student Confidence -> Placement Outcome	0.055	3.048	0.002	Supported
H4	Emerging Technology -> Student Preparedness -> Student Confidence -> Placement Outcome	0.044	3.021	0.003	Supported

Source: Author.

Table 6 depicts the mediation analysis results; the model test identified all expected relationships, which validated the strength of the role played by emerging technologies in determining the employability of students. There was a strong direct positive impact on Placement Outcomes (H1) by Emerging Technology, and the benefit was also significant on Student Preparedness (H2a) and Student Confidence (H3a). Preparedness (H2b) and Confidence (H3b), in turn, had a positive impact on Placement Outcomes, and thus, it is true that students who feel better prepared and confident perform better on their placement results. The mediation results also showed that Emerging Technology enhances Student Preparedness (H2) and Student Confidence (H3) indirectly to improve placement success. Also, the serial mediation route was important (H4), meaning that technology initially advances preparedness, which consequently increases confidence, resulting in improved placement outcomes. On the whole, the findings support the entire serial mediation model and indicate that technology-driven learning settings encourage the use of technologies in terms of employability and the use of essential psychological preparedness factors.

6. Discussion

By using Smart PLS and its conceptual features, the proposed study offers one of the first empirical studies on the effects of emerging technologies on the outcome of placements in higher education and specifically in Tamil Nadu (Mishra et al., 2022). According to the results, exposure to technology is a major factor in boosting the preparedness and confidence of students, which ultimately raises the chances of being placed (Schunk and DiBenedetto, 2020). The high correlation between emerging technology and preparedness ($b = 0.433$, $p < 0.001$) reflects the impact of AI-supported platforms, virtual labs, and digital simulations in the development of job-relevant competencies, which is also consistent with Kukulska-Hulme (2021). On the same note, the student confidence effect ($b = 0.287$, $p < 0.001$) demonstrates that the ability to use industry-oriented tools increases psychological preparedness (Dwivedi et al., 2021). The correlation between preparedness and confidence ($b = 0.537$, $p < 0.001$) is also another confirmation that mastery relates to self-efficacy (Bandura, 1997). The two mediators are also significant predictors of the placement outcomes ($b = 0.177$; $b = 0.191$), which confirms the claim of Jackson (2016) that behavioral and psychological competencies are at the center of employmentability. The positive influence of emerging technology on the results of placements ($b = 0.360$, $p < 0.001$) proves that the institutions with high priorities on digital capabilities and literacy are in a better place to increase the employability of students (Nguyen et al., 2020). Altogether, the results prove the emergent technology to be one of the key facilitators of successful placement, acting via direct and mediated mechanisms, and the necessity of the universities to enhance technology-based learning environments that cultivate preparedness and confidence among the students (Albelbisi et al., 2023).

7. Theoretical Implications

This study contributes to the literature on employability, educational technology, and student development by empirically demonstrating that emerging technology functions as an instructional tool and an enabling mechanism for psychological and behavioral outcomes, namely student preparedness and confidence, which are critical antecedents of placement outcomes. These findings support the Technology Acceptance and Employability Framework by showing that digital engagement in higher education influences career readiness in a measurable and multifaceted way (Dwivedi et al., 2021).

Second, from the methodological view, it validates the mediating roles of preparedness and confidence; the study integrates perspectives from educational psychology and career development. Drawing on Bandura's (1997) Social Cognitive Theory, the findings emphasize that self-efficacy developed through mastery experiences offered by educational technology serves as a key mechanism by which learning environments are translated into employability outcomes. Students who interact with AI-based simulations, virtual labs, and digital feedback systems build technical competencies and enhance their belief in their ability to perform successfully in job settings (Kukulska-Hulme, 2021).

Third, the study also offers support for the Theories utilized in the model (Fredrickson, 2001), which states that exposure to enriching and dynamic learning experiences through technology builds psychological resources such as self-confidence and readiness. In this context, technology is more than a medium of instruction; it becomes an agent of cognitive and emotional development that can shape career trajectories.

Finally, focusing on the regional higher education landscape of Tamil Nadu, the study addresses a critical gap in the global employability literature by contextualizing digital transformation within a developing economy (Albelbisi et al., 2023). Existing research often centers on Western educational settings; this study introduces empirical insights from India, where technology adoption in higher education is advancing rapidly but varies significantly across institutions (Mishra et al., 2022). As such, the findings enhance the theoretical understanding of how digital education impacts placement readiness in diverse contexts.

8. Managerial Implications

The findings provide meaningful implications for university administrators, placement coordinators, and curriculum designers aiming to enhance employability outcomes. Emerging technology should be understood as a teaching supplement and a strategic investment in institutional competitiveness and student success. Incorporating tools such as virtual labs, AI-based simulations, learning management systems, and job-readiness platforms into academic programs can significantly improve both the cognitive and psychological readiness of students (Bond et al., 2020)

Curriculum designers should ensure that these tools are integrated into mainstream coursework and assessment practices, aligning learning outcomes with current industry demands (Tondeur et al., 2017). Placement cells can partner with academic units to organize digitally enhanced workshops, mock interviews, and certification modules, all of which contribute to final-year students' preparedness and confidence (Nguyen et al., 2020).

These strategies can enhance institutional reputation and attract prospective students and recruiters who value digital fluency and real-world readiness (Tomlinson, 2017). Universities that align their pedagogical approaches with evolving technological trends will be better positioned to navigate the future of work and provide students with a competitive edge in placement processes (Jackson, 2016). To meet regulatory requirements, policymakers in Indian higher education, like AICTE and UGC, may require organized digital-readiness audits, market national competency frameworks, and reward institutions that show positive changes in employability. On the industry side, digitally-skilled analytics and simulation-based testing, and micro-credential validation can be incorporated into the hiring processes by recruiters to take advantage of the digital preparedness of students. Another way of measuring the ROI of the digital tools used in universities is through the placement conversion rate, level of satisfaction by employers with the results, and process improvement of student preparedness in the long run. All these measures contribute to the policy-practice linkage and improve technology-based employability outcomes.

9. Limitations and Suggestions for Future Studies

Despite the meaningful contributions of this study, several limitations are acknowledged. The data was collected from a few universities in Tamil Nadu, which may constrain the generalizability of the findings across other regions, institutional types, or cultural settings. Future research could extend this investigation to include a more diverse and geographically broad sample to strengthen external validity. Additionally, the cross-sectional design restricts the ability to establish causal relationships between the variables. Longitudinal studies could better capture the evolving influence of emerging technologies on student preparedness, confidence, and placement outcomes over time.

Using self-reported data introduces potential response biases, including social desirability effects. Objective indicators such as actual placement statistics, employer evaluations, or academic performance would better validate the observed relationships (Podsakoff et al., 2003). Moreover, emerging technology was treated as a unified construct in this study. Future research could deconstruct it into specific categories, such as artificial intelligence, virtual reality, and cloud computing, or learning management systems, to examine their unique effects on employability factors.

Further, including additional mediating or moderating variables, such as faculty mentorship, industry-academic partnerships, institutional reputation, or intrinsic student motivation, may help reveal more nuanced pathways through which technology influences placement outcomes. Such expansions would enrich the current model and offer a broader theoretical and practical understanding of student employability in the digital era.

10. Conclusion

This study examined the influence of emerging technologies on student placement outcomes in the context of higher education in Tamil Nadu, with student preparedness and confidence as key mediating factors. The results highlight that the strategic integration of technology within academic environments significantly enhances students' readiness for employment, both in terms of skill acquisition and psychological preparedness. These findings are consistent with previous research, which emphasizes that exposure to digital tools can foster career readiness by strengthening both technical and behavioral competencies. The study demonstrates that emerging technologies do more than improve learning delivery; they shape how confident and prepared students feel when entering the workforce, ultimately influencing placement success (Kukulska-Hulme, 2021).

In a competitive and technologically evolving job market, these findings underscore the need for higher education institutions to adopt targeted, technology-enhanced strategies that align curriculum development with industry expectations. By combining robust digital infrastructure with student-centered support systems, universities can position their graduates for sustained employability and career growth.

Beyond its practical recommendations, the research contributes to theoretical discourse at the intersection of digital education, career development, and psychological readiness. It offers a validated model for future academic and policy-related inquiries.

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