NATURALISTA CAMPANO
ISSN: 1827-7160
Volume 28 Issue 1, 2024

Enhancing Employability by Design: Optimizing Retention and Achievement in Indian Higher Education Institution

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Abstract: This research examines the intricate dynamics of Learning Analytics within Indian Higher Education Institutions, with a specific focus on the interplay among employee retention, academic performance, and employability. The study utilised a mixed methods convergent parallel design to conduct interviews with a wide range of academic participants from both public and private Higher Education Institutions (HEIs) in India. An analysis was conducted on 537 valid questionnaires in order to determine the correlations between these primary factors.

In order to validate the measurement model, exploratory and confirmatory factor analyses were conducted. Structural Equation Modelling (SEM) was utilised to provide explanations for the direct and mediated routes. The data presented significant and positive relationships, indicating that retention has a substantial impact on both attainment and employability, that attainment positively influences both retention and employability, and that attainment partially mediates the relationship between retention and employability.

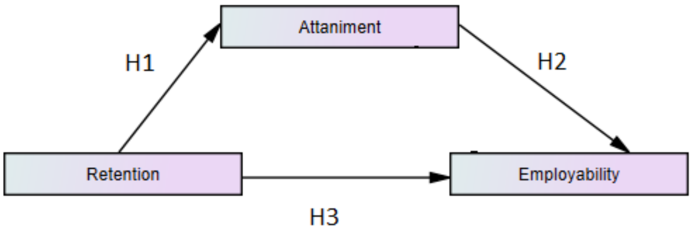
These studies provide nuanced observations regarding the factors influencing Learning Analytics in the higher education sector of India. As a result, academic institutions seeking to improve student performance and employability can draw practical conclusions from them. However, generalizability, instrument reliability, and the cross-sectional design of the study are acknowledged as limitations; therefore, longitudinal research is encouraged for a more comprehensive understanding.

Keywords: Higher Education, Learning Analytics, Retention, Attainment, Employability, Structural Equation Modelling (SEM), Mixed Methods.

1. Introduction

Learning analytics (LA) has evolved as a transformational subject within education, employing data-driven insights to improve teaching and learning outcomes. This literature review highlights significant topics, approaches, and conclusions from contemporary research on learning analytics. Overview of Learning Analytics: Learning analytics is described as "the measurement, collection, analysis, and reporting of data about learners and their contexts for purposes of understanding and optimising learning and the environments in which it occurs" (Siemens & Gasevic, 2012). This diverse discipline comprises a spectrum of data-driven ways to gather insights about student habits, engagement, and academic success. Scholarly work on learning analytics incorporates multiple research approaches. Quantitative studies generally exploit massive datasets to uncover patterns and relationships. Meanwhile, qualitative methods study the actual experiences and perspectives of students and educators in connection to learning analytics tools and interventions. Applications of Learning Analytics: Learning analytics has found applications across numerous educational settings. Research by Baker and Siemens (2014) has proven the efficiency of predictive analytics in detecting at-risk pupils, allowing prompt interventions to boost retention rates. Furthermore, research such as Johnson et al. (2017) has studied the use of learning analytics for adaptive learning, adapting instructional material to specific student requirements. Ethical concerns in learning analytics: As the usage of learning analytics continues to develop, ethical concerns have gained significance in the literature. Research by Anderson (2018) dives into concerns about data privacy and the proper use of student data in the context of learning analytics. These ethical problems underline the need for a balanced approach to ensuring that data-driven processes accord with ideals of justice and openness. Future Directions in Learning Analytics Research: Recent literature also indicates continuing debates regarding the future paths of learning analytics research. Researchers like Johnson (2020) urge a more nuanced understanding of the socio-cultural variables impacting the deployment and effectiveness of learning analytics technologies, providing new options for future investigation. The landscape of higher education is witnessing a dramatic transformation internationally, powered by innovations in technology and a growing emphasis on data-driven decision-making. In higher education in India, learning analytics, or LA, refers to the systematic use of data and analytics approaches to obtain insight into various components of the learning process. In order to assist decision-making and enhance the educational process, it comprises the collection, investigation, and interpretation of data supplied by students and educational institutions. Improving student achievements, retention rates, and institutional performance as a whole are the major goals. For instance, let us explore a fictional circumstance at a university in India. The college makes the choice to put in place a learning analytics system in order to understand and increase student performance. Gathering of Data: A multitude of sources, including the Learning Management System (LMS), online assessments, attendance records, and demographic data, are utilised by the institution to acquire data. Evaluation of Academic Performance: Learning analytics systems analyse students' academic performance by discovering patterns and trends in their quiz scores, turned-in assignments, and final grades. Early Intervention for Students Who Are at Risk: Predictive analytics is the process by which the system decides which children are most likely to perform badly academically. In the case that a student consistently gets low quiz scores and misses multiple classes, the Learning Analytics system may label them as "at risk." Tailored Educational Journeys: The institution may put tailored learning paths into place based on the data analysis. For example, if a student is having problems with a given topic, the system may offer extra resources, tutoring, or specialised interventions to fulfil their unique needs. Remarks for Teachers: For teachers, learning analytics also provide useful information. They may acquire information on how effectively their teaching tactics are functioning and alter their strategies in light of data-driven insights. Conformity to Employability Objectives: Learning Analytics is able to analyse employability-related factors in addition to academic performance. Monitoring students' engagement in extracurricular activities, internships, and career development classes, for example, may serve to offer a holistic picture of how prepared they are for the workforce. Making decisions at the institution: The combined data will enable university authorities to make well-informed judgements on curriculum updates, resource allocation, and general learning environment development methods. Learning Analytics (LA) resides at the confluence of these aspects, proposing to transform the educational environment by utilising data to enhance the learning experience and influence institutional strategy. In the environment of Indian higher educational institutions (HEIs), where different issues and potential meet, the integration and influence of learning analytics present intriguing considerations. This research attempts to examine "The Use and Influence of Learning Analytics in Indian Higher Educational Institutions," offering light on the existing degree of implementation, the issues faced, and the prospective ramifications for students, educators, and institutions. India, with its complex tapestry of cultures, languages, and educational expectations, presents a unique backdrop for the research of learning analytics in higher education. The country has undergone a large surge in enrollment in recent years, and the demand for great education is higher than ever. The adoption of learning analytics may potentially address many difficulties, ranging from student success and retention to institutional performance. However, despite the international momentum for adopting learning analytics, its incorporation into the Indian higher education system is still in its infancy. As we explore the implementation and impact of learning analytics in Indian HEIs, it is crucial to understand the wider educational context. The conventional pedagogical practices, heavily established in the Indian education system, are being challenged by the need for adaptability and innovation. Learning analytics, with its promise of data-driven insights, has the power to bridge the gap between traditional teaching methodologies and the rising needs of contemporary learners. Literature review: The quick expansion of the Indian higher education sector, driven by factors such as rising enrollments, globalization, and technological developments, has pushed the adoption of effective approaches to boost student learning outcomes and institutional performance. Learning analytics (LA) has emerged as a feasible way to overcome these issues by giving data-driven insights into student learning and institutional operations. This literature research attempts to evaluate the utilisation and impact of LA in Indian higher educational institutions (HEIs). Current Level of LA Adoption in Indian HEIs Despite the potential benefits of LA, its acceptance in Indian HEIs has been sluggish. Studies have indicated that a majority of Indian HEIs are still in the early stages of adopting LA, with minimal application and exploitation of LA tools and methodologies. This delayed acceptance may be attributed to numerous causes, including a lack of knowledge of LA and its potential advantages, a lack of competence in LA among academics and staff, data quality challenges, and privacy concerns. Factors Influencing LA Adoption Several elements have been observed to affect the adoption of LA at Indian HEIs. These qualities include institutional leadership, academic support, organisational culture, technological infrastructure, and financial resources (Fugate, Kinicki, & Ashforth, 2004; Ihantola et al., 2015; Jak & Cheung, 2018). Studies have suggested that competent institutional leadership, supportive faculty, and a positive organisational culture are beneficial to LA adoption. Impact of LA on Student Learning Outcomes Studies analysing the impact of LA on student learning outcomes have yielded mixed conclusions. Some studies have shown that LA may positively impact student learning results by offering tailored feedback, detecting at-risk pupils, and supporting instructional interventions. However, other studies have found limited or no impact of LA on student learning outcomes, suggesting that the effectiveness of LA is dependent on various factors, such as the type of LA used, the context of implementation, and the quality of data (Policies and practices for addressing barriers to student learning: Current status and new directions, n.d.; Rubin, Bell, & McClelland, 2017; Shahzad et al., 2020). Impact of LA on Institutional Effectiveness LA may also aid in increasing institutional effectiveness by delivering data-driven insights for better decision-making, enhancing resource allocation, and encouraging institutional responsibility. LA may be used to track student enrollment trends, identify areas of strength and weakness in academic programmes, and assess the success of instructional activities. Challenges and Future Directions Despite the tremendous potential of LA, numerous obstacles need to be addressed to facilitate its effective adoption and implementation in Indian HEIs. These issues include building a complete LA strategy, educating teachers and staff on LA, guaranteeing data privacy and security, and fostering a culture of data-driven decision-making. LA has emerged as a feasible technique to boost student learning outcomes and institutional performance in Indian HEIs. However, the sluggish acceptance and constrained implementation of LA in Indian HEIs require further attention and action. By resolving the problems and enabling effective implementation of LA, Indian HEIs may leverage the potential of data analytics to strengthen their teaching and learning processes, increase student accomplishment, and promote institutional performance. Conceptual and theoretical background The study focuses on the Social Cognitive Career Theory (SCCT) as a theoretical framework to explore the linkages between retention, achievement, and employability in the setting of learning analytics within Indian higher educational institutions. Developed by Albert Bandura, SCCT states that individuals' work decisions and performance are affected by a dynamic combination of personal attributes, contextual events, and behavioral patterns. In the context of this study: Retention: SCCT underlines the role of human traits, such as self-efficacy and outcome expectations, in shaping people's decisions to continue in a particular course of activity. Students who see themselves as capable of academic performance (self-efficacy) and anticipate good repercussions from their educational endeavours are more likely to display better retention rates. Attainment: SCCT highlights the relevance of learning experiences and performance accomplishments in creating self-efficacy beliefs. As students reach academic milestones and efficiently navigate their educational journey, their self-efficacy in academic domains is reinforced. Attainment, under the SCCT paradigm, becomes a crucial component in determining a person's career-related decisions and actions. Employability: SCCT believes that self-efficacy beliefs play a significant role in professional growth. Individuals with high self-efficacy in their academic endeavours are more likely to engage in behaviours that improve their employability, such as seeking out hard work, persisting in the face of adversity, and actively participating in career-related activities. The SCCT paradigm also stresses the function of observational learning, where individuals gain insights and adjust their behaviours by witnessing others in analogous settings. In the higher education environment, this may materialise via mentorship programmes, collaborative learning experiences, and exposure to successful academic and career trajectories. By adopting SCCT, the study fits with a theoretical approach that focuses on the dynamic and reciprocal connections between personal, behavioural, and environmental components. This paradigm provides a lens through which the implications of retention and accomplishment on employability may be studied, leading to a greater knowledge of the variables driving students' educational and professional pathways in the context of learning analytics.

Objectives:
1. To investigate the parameters impacting learning analytics in higher education institutions in India.
2. To examine how student achievement and retention impact students' employment
3. To explore how, in Indian HEIs, student achievement serves as a mediator between student retention and employability.



Conceptual Framework

Hypotheses:
H1: There is a strong influence of Retention on Attainment.
H2: There is a strong influence of Attainment on Employability.
H3: There is a strong influence of Retention" on Employability.

2. Methodology

Mixed techniques convergent parallel design employed for this project. The research population comprises all Higher Educational Institutions (HEIs) in India. There are two components to this survey. The first component presents the sample's demographics, as described in Table, and the second piece contains the sample's replies to the questions, which participants scored on a 5-point Likert scale, where one is strongly disagrees and five is strongly agree.

Technique of data analysis
In the present research, descriptive and inferential statistics were utilised. The description was generated by computation of the mean, standard deviation, percentage, and frequency distribution to assess the distribution of data.
The study's key tools are the Statistical Package for the Social Sciences (SPSS) and AMOS version 22. The structure of a set of measurable data was initially found via exploratory factor analysis. EFA also assists in establishing the construct validity of an instrument during its early development. Following the completion of the study's factors, the Confirmatory factor analysis (CFA) was performed to assess if the proposed scale was sufficient for the inquiry. The next stage was to undertake Structural Equation Modelling (SEM), a multivariate approach that concurrently assesses many regression equations to find the relationship between all of the study's variables. The model was examined simultaneously using mediation analysis and findings are reported in the following subsections.

3. Data analysis and Results

Demographic Information:

Table 1: Demographic profile of the respondents

Description	Items	Percentage
Gender	Male	49 %
	Female	51%
Age (years)	18-21	33%
	22-30	33%
	More than 31	34%
Years	1st year	10%
	2nd year	37%
	3rd year	24%
	4th year	29%
	Bachelor	33%
	Master	33%
	PhD	34%

Source: Primary survey

Exploratory Factor Analysis

The examination of variables impacting Learning Analytics in Indian Higher Educational Institutions uses an exploratory factor analysis (EFA) as the analytical tool. To determine the sample's adequacy, the Kaiser–Meyer–Olkin (KMO) test was run, providing a KMO statistic of 0.978, above the suggested threshold of 0.70 and validating the sufficiency of the sample. Additionally, the Bartlett test of sphericity, done at the 1% level of significance, further validated the adequacy of the sample.

For the study of thirteen variables, a Principal Component study (PCA) with Varimax Rotation Method Kaiser was performed. Normalization, as a required step for factor analysis, was conducted. Following a more severe factor selection criteria, where items with factor loadings below 0.60 were examined, it was discovered that all 13 items had factor loadings surpassing this level. Thus, none of the elements were omitted from the analysis. Post applying the criteria based on Eigenvalue above 1, three components were retrieved, explaining a total variance of 80.0%. Each component of the suggested instrument contributed to more than 60% of the total variance, suggestive of the procedure's success.

In addition, the internal consistency of a scale or test may be evaluated using Cronbach's alpha to assure that the measurements are trustworthy. This international rating of a measure's dependability is given by a coefficient with a value between 0 and 1. If all of the scale items are totally independent from one another then $\alpha = 0$; and, In the instance where the covariances among all of the variables are particularly high, then α will approach 1. A higher dependability score denotes a more trustworthy designed scale.

Response consistency across three factors is verified using Cronbach's alpha . Internal consistency may be tested using Cronbach's alpha, and a value above 0.70 (Nunnally, 1978) shows that the questionnaire has reliability and may be employed for further inquiry.

Table 1: KMO and Bartlett's Test

KMO and Bartlett's Test	
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	.978

Confirmatory factor analysis

The relationship between the research's latent factors and the study's observable variables is clarified by use of a Confirmation Factor Analysis. Using either theoretical considerations or empirical data, or both, canonical factor analysis (CFA) establishes hypotheses regarding the arrangement of variables and then runs statistical tests to see if they hold. Validity and reliability of the constructs were assessed using CFA, and the model was created based on a priori subject matter. While developing the CFA model, we considered each concept separately as an exogenous variable.

Model fit

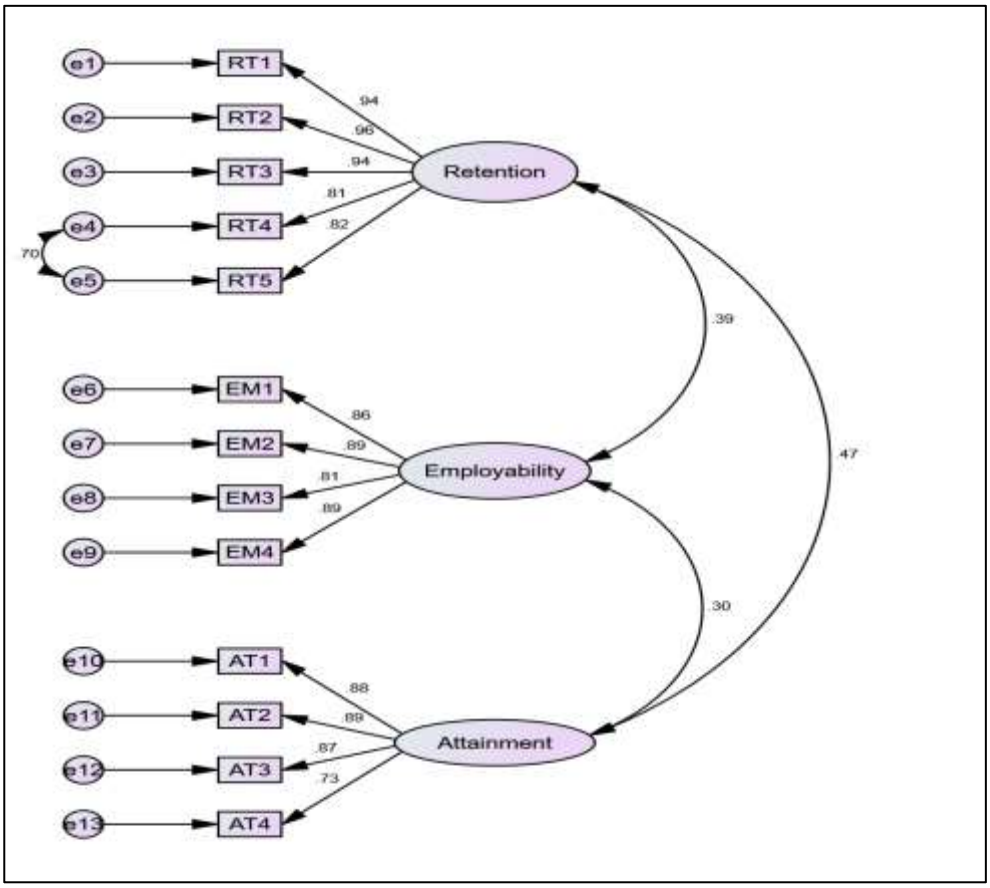
BelowTable-3 displays the outcomes of the overall fit statistics used in assessing the conceptual model. The great indicators of fit statistics such as CFI, NFI,GFI & AGFI with the bad indication RMSEA , all these measures are in the range that would be related with good fitness. These diagnostics suggest, model offers a reasonable overall fit.

Reliability and validity

Composite reliability (CR) and average variance extracted (AVE) are employed to quantify the convergent validity (CR). All AVE values are larger above the threshold of 0.50, proving the measurement model's convergent validity, which gives a range of 0.608 to 0.809. Additionally, the CR value of all the seven research components is above the threshold value of 0.7.

Discriminant validity establishes the lack of association between two ostensibly unrelated variables. Maximum shared variance (MSV) must be less than average variance extracted (AVE) for discriminant validity. As noted in Table 4, all MSV values are lower than ASV and that suggests sufficient discriminant validity.

Figure 2: CFA model for the proposed scale



Source: Primary Survey

Table 3: Goodness of Fit indices in CFA model

Indices	Abbreviation	Observed values	Recommended criteria
Goodness-of-fit index	GFI	0.942	>0.90
Adjusted GFI	AGFI	0.914	>0.80
Normed fit index	NFI	0.969	>0.90
Comparative fit index	CFI	0.980	>0.95
Root means square error of approximation	RMESA	0.064	<0.05 good fit <0.08 acceptable fit
Tucker-Lewis's index	TLI	0.975	0<TLI<1

Table 4: Composite Reliability, Convergent Validity & Discriminant Validity for Scale Items

	CR	ASV	MSV	Retention	Employability	Attainment
Retention	0.953	0.804	0.297	0.897		
Employability	0.921	0.745	0.394		0.863	
Attainment	0.906	0.708	0.473			0.841

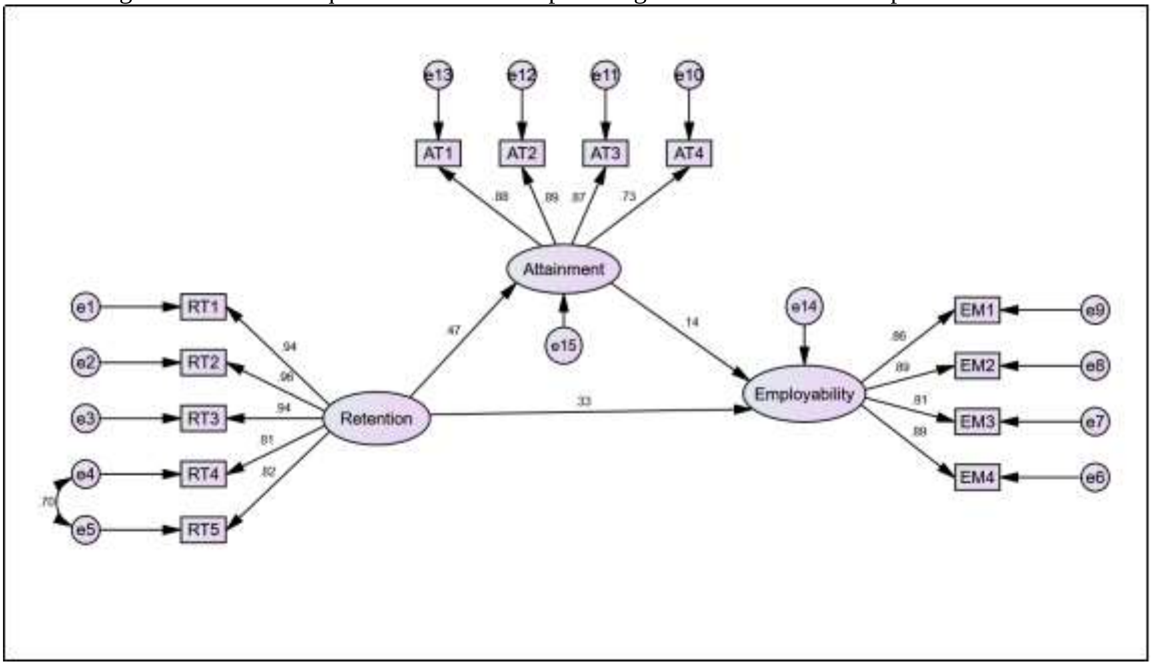
Hypotheses testing using SEM Model.

The research does SEM analysis using maximum likelihood approach to assess the causal association between learning analytics components. The influence of Retention as independent variable (exogenous) on student employability as dependent variable (endogenous) were investigated together with achievement as mediator between these two variables. The criterion for selection or rejection of research hypothesis based on crucial ratio value of path above ±1.96 and p value less than 0.05 at 5% level of significance.

Table 5 presents the outcomes of the route analysis and hypothesis testing. The standardized path coefficient and the p-value for each relationship are presented. By referring to Table 5 and Figure 3, it is established that the standardized path coefficient (β) of retention to achievement is positive and significant as β =0.473 with p=0.000. Since p value <0.05 and CR (9.307) >1.96, so hypothesis H1 accepted.

The influence of achievement on employability of student is positive and significant with β = 0.142, CR = 2.553 and p =0.011 ($p < 0.05$), given adequate evidence to support hypothesis H2. Similarly, retention significantly affected employability with β = 0.327, p= 0.000. This association is significant as p value less than 0.05, hence hypothesis H3 was supported by this result.
The coefficient of determination (R2) value is 0.355, for attainment estimated 35.5% of variance in attainment is explained by retention. The two predictors of employability, i.e. retention and achievement explained 42% of the overall variation in students' employability.
The fit indices of the measurement model are CMIN/df =2.779; p =0.000, RMSEA = 0.064, CFI = 0.970, NFI = 0.979 and AGFI = 0.924. The findings reveal that the structural model suits prediction and interpretation.

Figure: 3 Structure Equation Model - The path diagram with standardized parameters estimates



Source: Primary Survey

Table 5: Path coefficients of the Structural model

Hypo thesis	Outcome variables		Causal Variables	S.E.	C.R.	P	Path coefficient	Results
H1	Attainment	<---	Retention	.038	9.307	***	0.473	Supported
H2	Employability	<---	Attainment	.079	2.553	.011	0.142	Supported
H3	Employability	<---	Retention	.058	5.991	***	0.327	Supported

*Note: P refers to the differential probability. *= P<0.05, **p<0.01 & *** p<0.000*

Mediation analysis:
For the testing the influence of mediator variable Attainment on the relationship between retention and employability, the current study performed Mediation analysis using bias corrected confidence intervals (BC) method using 2,500 replicates of a bootstrap sample to determine the lower and upper boundaries of the 95% confidence interval that Preacher and Hayes proposed (2008). Table 6 displays the findings. In the bootstrapping approach, we evaluated the standard errors of the direct effect, the indirect impact, and the total effect. If $p < 0.05$, when both the direct and indirect effects are large, mediation is present (p 0.05), it suggests partial mediation; if the direct influence is non-significant ($p > 0.05$), it implies full mediation.
The data from table 6 demonstrated that Retention has a large indirect impact on Employability via Attainment. We may deduce that Attainment is substantially mediating between Retention and Employability. Since both standardized direct and indirect paths have p value below 0.05, thus, it is demonstrated that achievement partly mediates the relationship between Retention and Employability of the students. These statistics support the acceptance of hypothesis H4.

Table 6: Bootstrapped Results of Indirect Effects

Relationship	Standardized indirect effect	Standardized direct effect	Standardized total effect	Results
Attainment → Retention → Employability	0.0712	0.358	0.410	Partial mediation
	p = 0.035	p =0.002	p = 0.002	

Source; The authors

4. Discussion

The outcomes of the research add to the knowledge of the elements impacting Learning Analytics in Indian Higher Educational Institutions. The positive correlations discovered between Retention, Attainment, and Employability demonstrate the interconnection of these factors and their influence on the learning experience and students' future prospects.

Retention and Employability: The research supports the assumption that a greater retention rate significantly improves employability. This highlights the necessity of programmes targeted at keeping students, not just for academic performance but also for their long-term professional prospects.

Attainment and Employability: The beneficial influence of Attainment on Employability highlights the significance of academic accomplishment in influencing students' preparation for the workforce. Institutions are encouraged to develop educational experiences that contribute to students' skills and knowledge acquisition.

Mediation by Attainment: The identification of Attainment as a partial mediator stresses the relevance of academic performance in boosting employability. Institutions should concentrate not just on keeping students but also on enabling their academic successes to increase their employability.

Practical Implications: Institutions should develop focused efforts to boost retention rates, recognizing the beneficial ripple impact on students' employment.

Educational experiences and curriculum should be tailored to promote students' achievement, providing them with the required skills and information for future work.

Recognizing the mediating function of Attainment, institutions should encourage programmes that contribute to students' academic achievement.

5. Conclusion

In conclusion, this research gives useful insights into the elements impacting Learning Analytics in Indian Higher Educational Institutions. The positive correlations established among Retention, Attainment, and Employability illustrate the multidimensional character of these factors and their overall influence on students' educational path and future professions. The results add to the continuing conversation on refining teaching methods and supporting students' success in the constantly shifting environment of higher education in India. The practical implications mentioned may aid institutions in devising successful methods to maximise the learning experiences of their students. Further research and longitudinal studies are suggested to study the persistent influence of these characteristics over time and to develop methods for boosting student performance and employability in higher education.

Limitation:

While this research offers useful insights into the variables driving Learning Analytics in Indian Higher Educational Institutions, it is crucial to realise several limitations that may effect the generalizability and robustness of the results.

Firstly, the study population covers a varied variety of Higher Educational Institutions (HEIs) throughout India. However, the study's findings could not completely reflect the intricacies of unique institutional settings, and variances across institutions might alter the application of the conclusions to the overall higher education landscape in India.

Secondly, the survey instrument, however carefully created based on a comprehensive literature study, may have intrinsic limitations. The dependence on self-reported data from Respondents may induce answer biases, since views and interpretations of the questions might differ across respondents.

Furthermore, the research employed a mixed-methods convergent parallel design, and the quantitative data collection depended on a 5-point Likert scale. While this strategy gives numerical data for statistical analysis, it may not capture the richness and depth of qualitative insights that may be gathered via interviews or focus group discussions.

The generalizability of the results is hampered by the cross-sectional aspect of the research, limiting the capacity to establish causal links unequivocally. Longitudinal studies would be crucial in monitoring the persistent effect of retention, achievement, and employability over time.

Additionally, the research focused on a particular set of factors, including retention, accomplishment, and employability. Other possible elements impacting Learning Analytics, such as socio-economic origins, cultural variations, and technical infrastructure, were not specifically addressed in this study and may worth future examination.

Despite these limitations, the research makes vital contributions to the understanding of Learning Analytics in the Indian higher education setting. Future research attempts should examine resolving these constraints to give a more thorough and nuanced knowledge of the various processes at play in the uptake and effect of Learning Analytics in varied higher educational settings in India.

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