Journal of Research Administration
Society of Research Administrators International

LONGITUDINAL STUDY OF LEARNING ANALYTICS IMPLEMENTATION AND ITS IMPACT ON STUDENT OUTCOMES IN INDIAN HIGHER EDUCATION

Dr. Suganya.S
Assistant Professor, School of Management Studies, Reva University, Bengaluru

Ms Priyanka Joe
Assistant Professor, Department of Management Studies, Mount Carmel College, Autonomous, Bengaluru

Dr. Anilkumar.R
School of Management, Faculty of Management, Mount Carmel College, Autonomous, Bengaluru

Abstract
This study analyses the subtle dynamics of Learning Analytics in Indian Higher Educational Insti tutions, concentrating on the interaction between retention, achievement, and employability.
Employing a mixed methods convergent parallel design, the research questioned a broad population of academic respondents across public and private Higher Educational Institutions (HEIs) in India. A total of 537 usable questionnaires were evaluated to investigate the correlations between these main factors.
Exploratory and Confirmatory Factor Analyses were performed to verify the measurement model , while Structural Equation Modeling (SEM) explained the direct and mediated routes.
The data demonstrated positive and substantial connections, demonstrating that retention conside rably effects attainment and employability, attainment favourably impacts employability, and att ainment partly mediates the link between retention and employability.
These studies give subtle insights into the dynamics affecting Learning Analytics in the Indian higher education scene, giving practical implications for institutions looking to enhance student performance and employability. However, the study admits limits in generalizability, instrument reliability, and the cross-sectional character of the research, encouraging more longitudinal studies for a thorough understanding.
Keywords - Learning Analytics, Higher Education, Retention, Attainment, Employability, Struct ural Equation Modeling (SEM), Mixed Methods

Introduction

Learning Analytics (LA) has emerged as a transformative field within education, leveraging data-driven insights to enhance teaching and learning outcomes. This literature review explores key themes, methodologies, and findings from recent research on learning analytics.
Overview of Learning Analytics: Learning Analytics is defined as "the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (Siemens & Gasevic, 2012). This

multidisciplinary field encompasses a range of data-driven approaches to gain insights into student behaviors, engagement, and academic performance.

Scholarly work on learning analytics employs diverse research methodologies. Quantitative studies often leverage large datasets to identify patterns and correlations. Meanwhile, qualitative approaches explore the lived experiences and perceptions of students and educators in relation to learning analytics tools and interventions.

Applications of Learning Analytics: Learning analytics has found applications across various educational contexts. Research by Baker and Siemens (2014 demonstrated the effectiveness of predictive analytics in identifying at-risk students, enabling timely interventions to enhance retention rates. Furthermore, studies such as Johnson et al. (2017) have explored the use of learning analytics for adaptive learning, tailoring educational content to individual student needs.

Ethical Considerations in Learning Analytics: As the use of learning analytics continues to expand, ethical considerations have gained prominence in the literature. Research by Anderson (2018) delves into issues of data privacy and the responsible use of student data in the context of learning analytics. These ethical concerns highlight the need for a balanced approach to ensure that data-driven practices align with principles of fairness and transparency.

Future Directions in Learning Analytics Research: Recent literature also reflects ongoing discussions about the future directions of learning analytics research. Researchers like Johnson (2020) advocate for a more nuanced understanding of the socio-cultural aspects influencing the implementation and impact of learning analytics tools, opening up avenues for further exploration The landscape of higher education is experiencing a revolutionary transition globally, fueled by breakthroughs in technology and a greater focus on data-driven decision-making.

In higher education in India, learning analytics, or LA, refers to the methodical use of data and analytics techniques to get understanding of many facets of the learning process. In order to support decision-making and improve the educational process, it includes the gathering, examination, and interpretation of data produced by students and educational institutions. Improving student results, retention rates, and institutional performance as a whole are the main objectives.

For instance: Let us contemplate a fictitious situation at a university in India. The college makes the decision to put in place a learning analytics system in order to comprehend and enhance student performance.

Gathering of Data: A number of sources, including the Learning Management System (LMS), online tests, attendance logs, and demographic data, are used by the institution to gather data.

Evaluation of Academic Performance: Learning analytics systems evaluate students' academic performance by finding patterns and trends in their quiz results, turned in assignments, and final grades.

Early Intervention for Students Who Are at Risk: Predictive analytics is the method by which the system determines which pupils are most likely to do poorly academically. In the event that a student frequently has poor quiz results and skips many courses, the Learning Analytics system may identify them as "at risk."

Tailored Educational Journeys: The institution may put personalised learning routes into place based on the data analysis. For example, if a student is having difficulty with a certain subject, the system may suggest more materials, tutoring, or focused interventions to meet their individual requirements.

Remarks for Teachers: For instructors, learning analytics also provide insightful information. They may get input on how well their instructional strategies are working and modify their strategies in light of data-driven insights.

Conformity to Employability Objectives: Learning Analytics is able to evaluate employability-related criteria in addition to academic success. Monitoring students' involvement in extracurricular activities, internships, and career development courses, for example, may help to provide a comprehensive picture of how prepared they are for the workforce.

Making Decisions at the Institution: The combined data will help university officials make well-informed judgements on curriculum updates, resource allocation, and general learning environment enhancement tactics.

Learning Analytics (LA) lies at the crossroads of these factors, offering to alter the educational environment by harnessing data to improve the learning experience and guide institutional strategy. In the setting of Indian Higher Educational Institutions (HEIs), where varied problems and possibilities combine, the integration and effect of Learning analytics offer fascinating considerations.

This study intends to look into "The Use and Influence of Learning Analytics in Indian Higher Educational Institutions," giving light on the present level of implementation, the problems encountered, and the possible repercussions for students, educators, and institutions.

India, with its diverse tapestry of cultures, languages, and educational demands, gives a unique context for the exploration of Learning Analytics in higher education. The nation has experienced a huge growth in enrollment in recent years, and the need for excellent education is stronger than ever.

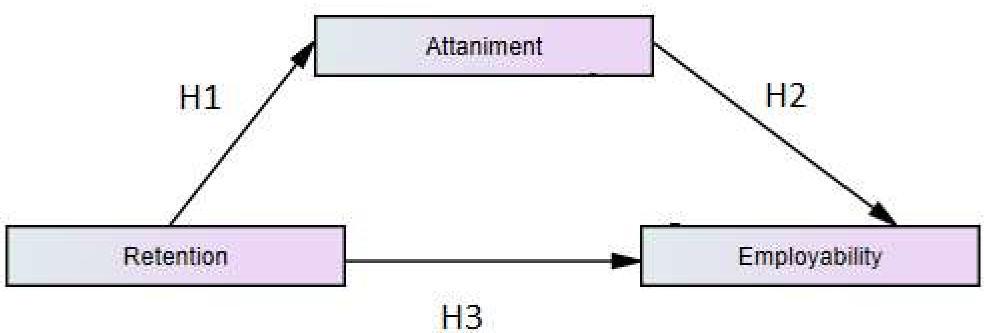
The application of Learning Analytics might possibly solve different challenges, ranging from student success and retention to institutional performance. However, despite the worldwide momentum in embracing learning analytics, its integration into the Indian higher education system is still in its infancy. As we study the application and effect of Learning Analytics in Indian HEIs, it is vital to understand the larger educational environment. The old pedagogical approaches, strongly embedded in the Indian education system, are being challenged by the need for adaptation and innovation. Learning Analytics, with its promise of data-driven insights, has the ability to bridge the gap between conventional teaching approaches and the increasing demands of modern learners. Literature review: The fast development of the Indian higher education sector, driven by factors such as expanding enrollments, globalization, and technology improvements, has prompted the adoption of effective measures to enhance student learning outcomes and institutional performance.

Learning analytics (LA) has emerged as a viable approach to solve these difficulties by delivering data-driven insights into student learning and institutional processes. This literature study intends to explore the usage and effect of LA in Indian higher educational institutions (HEIs). Current Level of LA Adoption in Indian HEIs Despite the potential advantages of LA, its uptake in Indian HEIs has been gradual. Studies have demonstrated that a majority of Indian HEIs are still in the early phases of adopting LA, with little application and exploitation of LA tools and approaches. This slow adoption can be attributed to various factors, including lack of awareness of LA and its potential benefits, lack of expertise in LA among faculty and staff, data quality issues, and privacy concerns. Factors Influencing LA Adoption Several variables have been discovered to impact the adoption of LA in Indian HEIs. These characteristics include institutional leadership, academic support, organizational culture, technical infrastructure, and financial resources (Fugate, Kinicki, & Ashforth, 2004; Ihantola et al., 2015; Jak & Cheung, 2018). Studies have indicated that good institutional leadership, supporting faculty, and a favourable organizational culture are conducive to LA adoption. Impact of LA on Student Learning Outcomes Studies evaluating the influence of LA on student learning outcomes have given conflicting findings. Some studies have demonstrated that LA may favourably improve student learning outcomes by giving customised feedback, identifying at-risk students, 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 help to institutional effectiveness by offering data-driven insights for better decision-making, boosting resource allocation, and fostering institutional accountability. LA may be used to monitor student enrollment patterns, identify areas of strength and weakness in academic programs, and analyse the efficacy of instructional initiatives. Challenges and Future Directions Despite the exciting potential of LA, various issues need to be addressed to encourage its successful acceptance and application in Indian HEIs. These challenges include developing a comprehensive LA strategy, training faculty and staff on LA, ensuring data privacy and security, and fostering a culture of data-driven decision-making. LA has emerged as a viable strategy to increase student learning outcomes and institutional performance in Indian HEIs. However, the delayed uptake and restricted application of LA in Indian HEIs need greater attention and action. By addressing the difficulties and supporting successful implementation of LA, Indian HEIs may use the potential of data analytics to better their teaching and learning processes, boost student achievement, and promote institutional performance. Conceptual and Theoretical Background The research focuses upon the Social Cognitive Career Theory (SCCT) as a theoretical framework to examine the links between retention, achievement, and employability in the context of Learning Analytics inside Indian Higher Educational Institutions. Developed by Albert Bandura, SCCT claims that people' job choices and results are impacted by a dynamic interaction of personal characteristics, environmental situations, and behavioral patterns. In the context of this study: Retention: SCCT stresses the relevance of human characteristics, such as self-efficacy and result expectancies, in moulding people' choices to continue in a given course of action. Students who regard themselves as capable of academic achievement (self-efficacy) and expect favourable consequences from their educational efforts are more likely to demonstrate greater retention rates. Attainment: SCCT underlines the value of learning experiences and performance successes in establishing self-efficacy beliefs. As students attain academic milestones and effectively navigate their educational path, their self-efficacy in academic areas is reinforced. Attainment, under the SCCT paradigm, becomes a major component affecting people' career-related choices and behaviours. Employability: SCCT proposes that self-efficacy beliefs play a vital role in professional development. Individuals with high self-efficacy in their academic endeavours are more likely to participate in behaviors that promote their employability, such as seeking out hard work, enduring in the face of challenges, and actively engaging in career-related activities. The SCCT paradigm also highlights the role of observational learning, where people acquire insights and alter their actions by seeing others in comparable circumstances. In the higher education context, this might materialise via mentoring programs, collaborative learning experiences, and exposure to successful academic and professional pathways. By using SCCT, the research corresponds with a theoretical viewpoint that stresses the dynamic and reciprocal interactions between personal, behavioral, and environmental components.

This paradigm offers a lens through which the implications of retention and achievement on employability may be investigated, leading to a fuller understanding of the determinants driving students' educational and professional paths in the context of Learning Analytics.

Objectives:

1. To determine the elements influencing learning analytics in higher education institutions in India.
2. To research how student attainment and retention affect students' employability
3. To investigate how, in Indian HEIs, student attainment functions 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.

METHODOLOGY

Mixed approaches convergent parallel design applied for this project. The research population encompasses all Higher Educational Institutions (HEIs) in India. There are two components to this survey. The first component offers the sample's demographics, as mentioned in Table, and the second section comprises the sample's answers to the questions, which participants assessed on a 5-point Likert scale, where one is strongly disagrees and five is strongly agree.

Technique of data analysis

In the current study, descriptive and inferential statistics were applied. The description was developed by calculation of the mean, standard deviation, percentage, and frequency distribution to examine the distribution of data.

The study's major tools include the Statistical Package for the Social Sciences (SPSS) and AMOS version 22. The structure of a collection of measured data was originally uncovered using exploratory factor analysis. EFA also aids in demonstrating the construct validity of an instrument during its early development. Following the conclusion of the study's factors, the Confirmatory factor analysis (CFA) was employed to determine whether the recommended scale was adequate for the inquiry. The next step was to do Structural Equation Modelling (SEM), a multivariate method that simultaneously evaluates several regression equations to determine the link between all of the study's variables. The model was evaluated jointly with mediation analysis and results are provided in the following subsections.

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

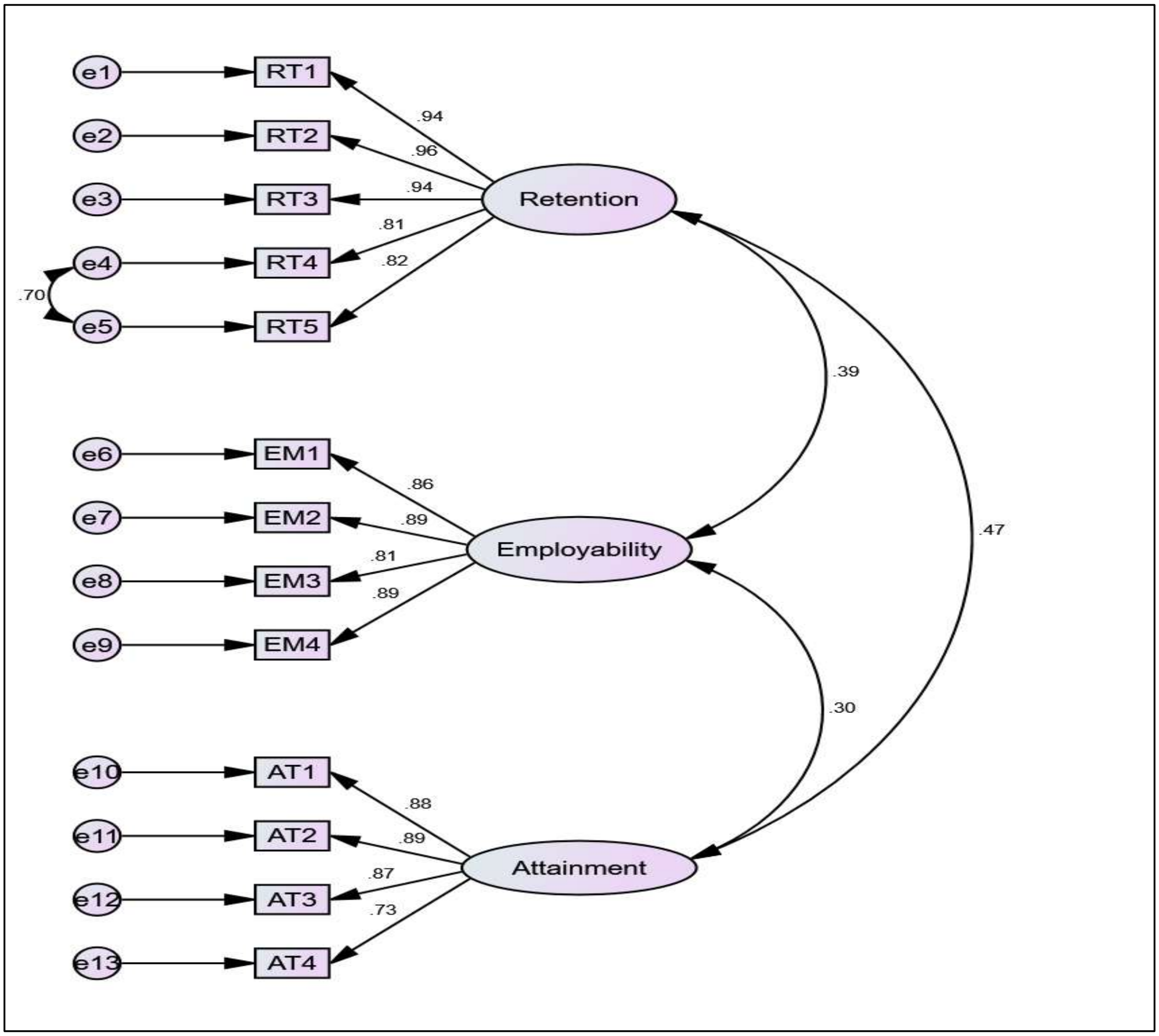
Table 3 displays the outcomes of the overall fit statistics used in assessing the conceptual model. The great indicators of fit statistics such as CFI, NFI,GFI & AGFI with the bad indication RMSEA , all these measures are in the range that would be related with good fitness. These diagnostics suggest,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

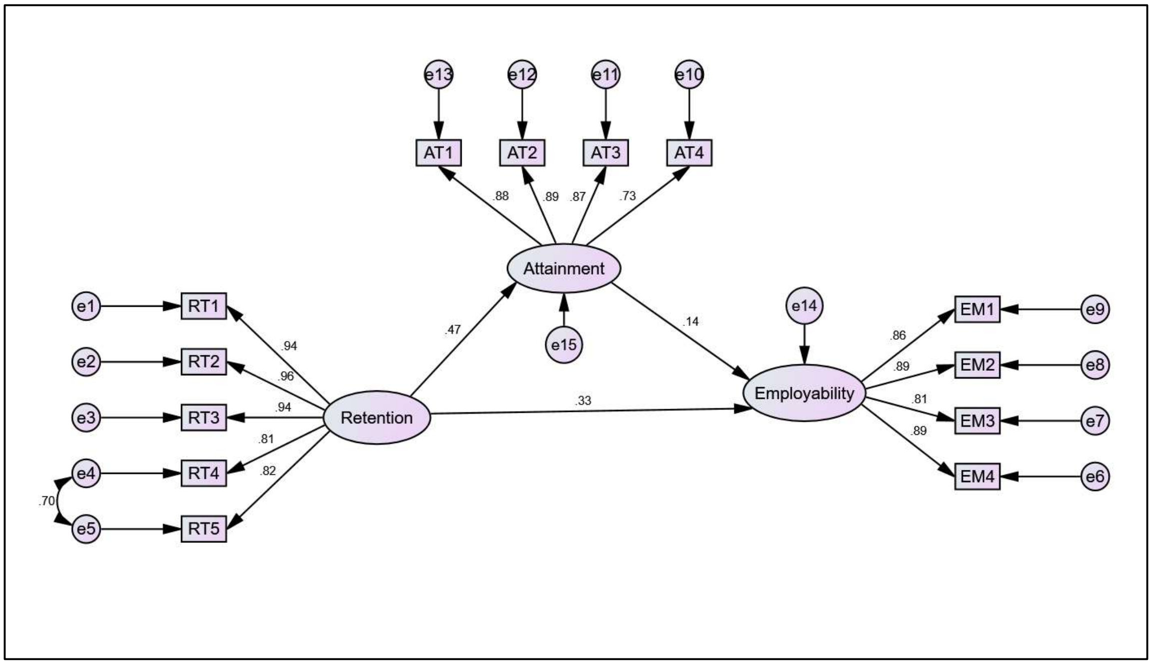
Table 5 presents the outcomes of the route analysis and hypothesis testing. The standardized path coefficient and the p-value for each relationship are presented. By referring to Table 5 and Figure 3, it is established that the standardized path coefficient (β) of retention to achievement is positive 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 illustrates the results. In the bootstrapping technique, we estimated the standard errors of the direct effect, the indirect impact, and the overall effect. If p < 0.05, when both the direct and indirect effects are substantial, mediation is present (p 0.05), it indicates partial mediation; if the direct impact is non-significant (p > 0.05), it implies complete mediation.

The data from table 6 indicated that Retention has a considerable indirect influence on Employability via Attainment. We may infer that Attainment is considerably mediating between Retention and Employability. Since both standardized direct and indirect pathways have p value below 0.05, therefore, it is established that attainment somewhat mediates the link between Retention and Employability of the students. These data support the adoption of hypothesis H4.

Table 6: **Bootstrapped Results of Indirect Effects**

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

Source; The authors

Discussion: The findings of the study contribute to the understanding of the factors influencing Learning Analytics in Indian Higher Educational Institutions. The positive relationships established between Retention, Attainment, and Employability highlight the interconnectedness of these variables and their impact on the learning experience and students' future prospects.

Retention and Employability: The study supports the idea that a higher retention rate positively influences employability. This underscores the importance of strategies aimed at retaining students, not only for academic success but also for their long-term career prospects.

Attainment and Employability: The positive impact of Attainment on Employability emphasizes the role of academic achievement in shaping students' readiness for the workforce. Institutions are encouraged to enhance educational experiences that contribute to students' skills and knowledge acquisition.

Mediation by Attainment: The identification of Attainment as a partial mediator emphasizes the importance of academic success in enhancing employability. Institutions should focus not only on retaining students but also on facilitating their academic achievements to boost their employability.

Practical Implications: Institutions should implement targeted strategies to improve retention rates, recognizing the positive ripple effect on students' employability.

Educational experiences and curricula should be designed to enhance students' attainment, providing them with the necessary skills and knowledge for future employment.

Recognizing the mediating role of Attainment, institutions should prioritize initiatives that contribute to students' academic success.

Conclusion

In conclusion, this study provides valuable insights into the factors influencing Learning Analytics in Indian Higher Educational Institutions. The positive relationships established among Retention, Attainment, and Employability highlight the multifaceted nature of these variables and their collective impact on students' educational journey and future careers. The findings contribute to the ongoing discourse on enhancing educational practices and fostering students' success in the dynamically evolving landscape of higher education in India. The practical implications outlined can guide institutions in formulating effective strategies to optimize the learning experiences of their students. Further research and longitudinal studies are recommended to explore the sustained impact of these factors over time and to refine strategies for promoting student success and employability in higher education.

Limitation:

While this study provides valuable insights into the factors influencing Learning Analytics in Indian Higher Educational Institutions, it is essential to acknowledge certain limitations that may impact the generalizability and robustness of the findings.

Firstly, the research population includes a diverse range of Higher Educational Institutions (HEIs) in India. However, the study's findings might not fully capture the nuances of specific institutional contexts, and variations among institutions could affect the applicability of the results to the entire higher education landscape in India.

Secondly, the survey instrument, though carefully constructed based on an exhaustive literature review, may have inherent limitations. The reliance on self-reported data from Respondents may introduce response biases, as perceptions and interpretations of the questions could vary among respondents.

Furthermore, the study utilized a mixed-methods convergent parallel design, and the quantitative data collection relied on a 5-point Likert scale. While this approach provides numerical data for statistical analysis, it may not capture the richness and depth of qualitative insights that could be obtained through interviews or focus group discussions.

The generalizability of the findings is constrained by the cross-sectional nature of the study, limiting the ability to establish causal relationships definitively. Longitudinal studies would be instrumental in tracking the sustained impact of retention, attainment, and employability over time.

Additionally, the study focused on a specific set of variables, namely retention, attainment, and employability. Other potential factors influencing Learning Analytics, such as socio-economic backgrounds, cultural differences, and technological infrastructure, were not explicitly addressed in this research and may warrant further exploration.

Despite these limitations, the study offers valuable contributions to the understanding of Learning Analytics in the Indian higher education context. Future research endeavors should consider addressing these limitations to provide a more comprehensive and nuanced understanding of the intricate dynamics at play in the adoption and impact of Learning Analytics in diverse higher educational settings in India.

References:

Fugate, M., Kinicki, A. J., and Ashforth, B. E. (2004). Employability: a psycho-social construct, its dimensions, and applications. Journal of Vocational Behavior, 65(1), 14–38. doi: 10.1016/j.jvb.2003.10.005.

Chen, J., & Li, W. (2011). A study on the relationship between college students' career values, self-efficacy, and employability. Exploration in Higher Education, 5(2), 106–110. doi: 10.3969/j.issn.1673-9760.2011.05.023.

Cole, A. W., Lennon, L., & Weber, N. L. (2019). Student perceptions of online active learning practices and the online learning climate predict online course engagement. Interactive Learning Environments, 29(5), 866-880. https://doi.org/10.1080/10494820.2019.1619593

Cooper, M., Ferguson, R., & Wolff, A. (2016). What can analytics contribute to accessibility in E-learning systems and to disabled students' learning? Proceedings of the Sixth International Conference on Learning Analytics & Knowledge - LAK '16. https://doi.org/10.1145/2883851.2883946

Dym, C. L., Agogino, A. M., Eris, O., Frey, D. D., & Leifer, L. J. (2005). Engineering design thinking, teaching, and learning. Journal of Engineering Education, 94(1), 103-120. https://doi.org/10.1002/j.2168-9830.2005.tb00832.

Basha, S. M., Kethan, M., & Aisha, M. A. (2021). A Study on Digital Marketing Tools amongst the Marketing Professionals in Bangalore City. JAC: A Journal of Composition Theory, 14(9), 17-23.

Kethan, M., et al. "A study on issues and challenges on production of handloom sector with special reference to rayalaseema and coastal region of Andhra Pradesh." IJAR 8.6 (2022): 89-95.

Kumar, T. Siva, and S. Sekhar. "Impact of e-Marketing on Influencing Consumer Purchase decision." International Journal of Scientific Development and Research 4.11 (2019).

Rana, Sarita. "Consumer Awareness and Perception Towards Green Marketing: An Empirical Study In Bangalore City." Journal of Positive School Psychology http://journalppw.com 6.5 (2022): 4240-4245.

Nethala, Vijaya Jyothi, Mr Firozkhan I. Pathan, and Mr S. Chandra Sekhar. "A Study on Cooperative Banks in India with Special Reference to Marketing Strategies." Journal of Contemporary Issues in Business and Government Vol 28.04 (2022).

Basha, S. M., & Ramaratnam, M. S. (2017). Construction of an Optimal Portfolio Using Sharpe's Single Index Model: A Study on Nifty Midcap 150 Scrips. Indian Journal of Research in Capital Markets, 4(4), 25-41.

Agrawal, D. K. (2022). An Empirical Study On Socioeconomic Factors Affecting Producer's

Participation In Commodity Markets In India. Journal of Positive School Psychology, 2896-2906.

Shaik, M. B., Kethan, M., Jaggaiah, T., & Khizerulla, M. (2022). Financial Literacy and Investment Behaviour of IT Professional in India. East Asian Journal of Multidisciplinary Research, 1(5), 777-788.

Basha, M., Singh, A. P., Rafi, M., Rani, M. I., & Sharma, N. M. (2020). Cointegration and Causal relationship between Pharmaceutical sector and Nifty–An empirical Study. PalArch's Journal of Archaeology of Egypt/Egyptology, 17(6), 8835-8842.

DrSanthosh Kumar, V., & Basha, S. M. (2022). A study of Emotional Intelligence and Quality of Life among Doctors in PandemicCovid 19. International Journal of Early Childhood, 14(02), 2080-2090.

Krishnamoorthy, D. N., & Mahabub Basha, S. (2022). An empirical study on construction portfolio with reference to BSE. Int J Finance Manage Econ, 5(1), 110-114.

JagadeeshBabu, M. K., SaurabhSrivastava, S. M., & AditiPriya Singh, M. B. S. (2020). Influence of social media marketing on buying behavior of millennial towards smart phones in bangalore city. PalArch's Journal of Archaeology of Egypt/Egyptology, 17(9), 4474-4485.

Shaik, M. B., Kethan, M., Rani, I., Mahesh, U., Harsha, C. S., Navya, M. K., & Sravani, D. (2022). Which determinants matter for capital structure? an empirical study on NBFC'S in India. International Journal of Entrepreneurship, 26, 1-9.

Mohammed, B. Z., Kumar, P. M., Thilaga, S., & Basha, M. (2022). An Empirical Study On Customer Experience And Customer Engagement Towards Electric Bikes With Reference To Bangalore City. Journal of Positive School Psychology, 4591-4597.

Basha, S. M., & Kethan, M. (2022). Covid-19 pandemic and the digital revolution in academia and higher education: an empirical study. Eduvest-Journal of Universal Studies, 2(8), 1-648.

Kethan, M., & Basha, M. (2022). Relationship of Ethical Sales Behaviour with Customer Loyalty, Trust and Commitment: A Study with Special Reference to Retail Store in Mysore City. East Asian Journal of Multidisciplinary Research, 1(7), 1365-1376.

Shaik, M. B., Kethan, M., & Jaggaiah, T. (2022). Financial Literacy and Investment Behaviour of IT Professional With Reference To Bangalore City. Ilomata International Journal of Management, 3(3), 353-362.

Kumarai, G. S., Bajaj, P. K., Rana, S. S., Basha, M., & Karumuri, V. (2022). An empirical study on customer satisfaction towards organized Retail outlets in Bengaluru city, Karnataka. Academy of Marketing Studies Journal, 26(5).

Basha, S. M., Kethan, M., & Aisha, M. A. (2021). A Study on Digital Marketing Tools amongst the Marketing Professionals in Bangalore City. JAC: A Journal of Composition Theory, 14(9), 17-23.

Kethan, M., & Basha, M. (2023). Impact of Indian Cinema on Youths Lifestyle and Behavior Patterns. East Asian Journal of Multidisciplinary Research, 2(1), 27-42.

Kethan, M., Khizerulla, M., Sekhar, S. C., & Basha, M. (2022). A study on issues and challenges on production of handloom sector with special reference to rayalaseema and costal region of Andhra Pradesh. IJAR, 8(6), 89-95.

Shaik, M. (2023). Impact of artificial intelligence on marketing. East Asian Journal of Multidisciplinary Research, 2(3), 993-1004.

Isac Gunday, D. M. K. (2023). A study on consumer perception towards fast food retail outlets with reference to bengaluru karnataka. Journal of Pharmaceutical Negative Results, 418-424.

Reddy, K., SN, M. L., Thilaga, S., & Basha, M. M. (2023). Construction Of An Optimal Portfolio Using The Single Index Model: An Empirical Study Of Pre And Post Covid 19. Journal of Pharmaceutical Negative Results, 406-417.

Basha, M., Kethan, M., Karumuri, V., Guha, S. K., Gehlot, A., & Gangodkar, D. (2022, December). Revolutions of Blockchain Technology in the Field of Cryptocurrencies. In 2022 11th International Conference on System Modeling & Advancement in Research Trends (SMART) (pp. 761-764). IEEE.

Ihantola, P., Vihavainen, A., Ahadi, A., Butler, M., Börstler, J., Edwards, S. H., Isohanni, E., Korhonen, A., Petersen, A., Rivers, K., Rubio, M. Á., Sheard, J., Skupas, B., Spacco, J., Szabo, C., & Toll, D. (2015). Educational data mining and learning analytics in programming. Proceedings of the 2015 ITiCSE on Working Group Reports. https://doi.org/10.1145/2858796.2858798

Jak, S., & Cheung, M. W. (2018). Meta-analytic structural equation modeling with moderating effects on SEM parameters. https://doi.org/10.31234/osf.io/ce85j

Jayaprakash, S. M., Moody, E. W., Lauría, E. J., Regan, J. R., & Baron, J. D. (2014). Early alert of academically at-risk students: An open-source analytics initiative. Journal of Learning Analytics, 1(1), 6-47. https://doi.org/10.18608/jla.2014.11.3

Kahu, E. R. (2013). Framing student engagement in higher education. Studies in Higher Education, 38(5), 758-773. https://doi.org/10.1080/03075079.2011.598505

Li, K., Peng, M. Y., Du, Z., Li, J., Yen, K., & Yu, T. (2020). Do specific pedagogies and problem-based teaching improve student employability? A cross-sectional survey of college students. Frontiers in Psychology, 11. https://doi.org/10.3389/fpsyg.2020.01099.

Macfadyen, L. P., & Dawson, S. (2010). Mining LMS data to develop an “early warning system” for educators: A proof of concept. Computers & Education, 54(2), 588-599. https://doi.org/10.1016/j.compedu.2009.09.008

Mustaffa, N., Said, M. N., Ismail, Z., & Tasir, Z. (2018). Framework for integrating algebraic thinking in problem-based learning via an online environment for school students. 2018 IEEE International Conference on Teaching, Assessment, and Learning for Engineering (TALE). https://doi.org/10.1109/tale.2018.8615390

Nunn, S., Avella, J. T., Kanai, T., & Kebritchi, M. (2016). Learning analytics methods, benefits, and challenges in higher education: A systematic literature review. Online Learning, 20(2). https://doi.org/10.24059/olj.v20i2.790.

Policies and practices for addressing barriers to student learning: Current status and new directions. (n.d.). PsycEXTRA Dataset. https://doi.org/10.1037/e573822011-001

Rubin, J. D., Bell, S., & McClelland, S. I. (2017). Graduate education in qualitative methods in U.S. psychology: Current trends and recommendations for the future. Qualitative Research in Psychology, 15(1), 29-50. https://doi.org/10.1080/14780887.2017.1392668

Shahzad, M., Qu, Y., Ur Rehman, S., Zafar, A. U., Ding, X., and Abbas, J. (2020). Impact of knowledge absorptive capacity on corporate sustainability with the mediating role of CSR: analysis from the Asian context. Journal of Environmental Planning and Management, 63(1), 148–174. doi: 10.1080/09640568.2019.1575799.

Sikor, A. B., Ibrahim, S. B., Hashim, M. H., & Madar, A. R. (2012). Learning techniques among adult students in higher learning institutions, Ministry of Higher Education India. Journal of Studies in Education, 2(4). https://doi.org/10.5296/jse.v2i4.2097

Troussas, C., Krouska, A., & Virvou, M. (2019). Using a multi-module model for learning analytics to predict learners' cognitive states and provide tailored learning pathways and assessment. Machine Learning Paradigms, 9-22. https://doi.org/10.1007/978-3-030-13743-4_2

Tamura, K., et al. (2019). Integrating multimodal learning analytics and inclusive learning support systems for people of all ages. Cross-Cultural Design. Culture and Society, 469-481. https://doi.org/10.1007/978-3-030-22580-3_35