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The Use and influence of Learning Analytics in Higher Educational Institutions: A Mediation Model of Student Attainment between Student Retention and Student Employability.

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Abstract

Purpose: The goals of this article are to (1) identify factors influencing Learning Analytics in Bengaluru HEIs and (2) examine the mediating role of Student Attainment in the relationship between Student Retention and Student Employability in Higher Educational Institutions (HEIs).
Design/methodology/approach – This research assembles and synthesizes data on the application of learning analytics. Learning analytics is the subject of empirical studies, including Public and private higher education institutions in Bengaluru were each sent one of 485 questionnaires. In total, 450 Chancellery, Dean, HOD, and Directors participated and completed the survey. Thirteen questionnaires were eliminated from the analysis because of missing data or outliers discovered during the data screening process. We could sift through 437 surveys, making up the final sample. The study runs SEM analysis using the maximum likelihood method to test the causal relationship between learning analytics factors. The impact of retention as the independent variable (exogenous) on student employability as the dependent variable (endogenous) was tested along with attainment as a mediator between these two variables.

Findings: Evidence demonstrates how learning analytics may assist educational institutions in making better use of data for decision-making. The findings revealed that retention significantly indirectly affects Employability through Attainment. Attainment is significantly mediating between Retention and Employability. Since both standardized direct and indirect paths have a p-value below 0.05, thus, it is confirmed that attainment partially mediates the relationship between Retention and Employability of the students.
Originality/value: The current study has explored retention, attainment, and employability as the critical factors that must be considered before applying Learning Analytics in Higher Educational Institutions. The research results confirmed that students' employability is significantly influenced by retention and attainment. Educational institutions and academics, particularly those working in open and distance settings, should use the study's findings to stay abreast of this developing subject and provide the groundwork for further research.

Keywords -Higher education, Learning analytics, Retainment, Attainment, Employability

1.1 Introduction

The term "learning analytics" (LA) is used to describe the practice of gathering, analyzing, and reporting business data for use in planning and decision-making (Campbell & Oblinger, 2007). Because of the prevalence of digital tools including learning management systems, student information systems, social media, and lecture capture systems have become more widely used in schools, this has resulted in the collection of vast amounts of data on instructional methods (Campbell, J.P 2007).
Despite the widespread use of LA in various types of schools, most of the writing on the topic has concentrated on the more traditional, face-to-face education. Even though the use of LA is just getting started in Bengaluru, there have already been a few studies that highlight the significant contributions of LA in Bengaluru HEIs. The literature on this topic is extensive (Clow, 2012; Tasir et al., 2016; Wong, 2017). Strategic guidance and effective leadership techniques are crucial for achieving long- term success in the deployment of LA and ensuring its optimal use. According to Rick(2013), it is possible to lessen opposition by addressing potential disputes and preparing for them from the outset of the LA modification process. As a result, institutions must take the initiative to alter and solve obstacles before fully embracing and accepting LA and its benefits for students, faculty, and other stakeholders (Tasir et al., 2016). In Bengaluru HEIs, stakeholders' openness to the dramatic changes brought about by digital technology is also crucial (Wong, 2017).

1.2 Aims and objectives

The paper examines the factors affecting learning analytics. There is also an analysis studying the impact of Students Retention and Students Attainment on Student Employability and finding the mediation effect of Students Attainment between Students Retention and Students Employability in Bengaluru HEIs.

2.1 Related Research

LA (Learning analytics) has recently emerged as an essential issue in technology- enhanced learning and teaching in higher education. Numerous studies have producedvarious techniques for applying LA (Zilvinskis, Borden, Barefoot & Kinzie, 2017). The research community is therefore asked to have a firm grasp on the types of outcomes they anticipate and use that information to guide their decisions about which LA initiatives to execute. However, the resources or capacity necessary to establish quality assurance in higher education can significantly impact theeffectiveness and sustainability of such efforts. Statistical testing, explanatory and predictive models and data visualization are just a few examples of LA's data and analytic methods (Arroway et al., 2016). The data-driven analysis can then inform decisions by many stakeholders, including faculty, administration, and students. Sincethere is no agreed-upon method for implementing LA, several strategies have been used for different ends. The question of "how do we begin the process for the adoption of institutional learning analytics?" is frequently raised in response to the difficulty posed by LA's varied implementation for educational institutions that hope to participate.

There has been an uptick in the number of published case studies dealing with the application of LA to the context of higher education. However, only a few reviews provide a summary of these isolated investigations. Dyckhoff (2011), for example, discussed the study' guiding questions and techniques. According to the results, previous research has addressed six distinct inquiry categories.

Nunn et al. (2016) analyzed LA's techniques, advantages, and disadvantages. Visual data analysis, social network analysis and semantic analysis were all discovered to be in use. Students, teachers, and administrators all saw gains in areas like course selection, pedagogical practices, assessment, assessment practices, student learning outcomes, teacher effectiveness, student engagement, post-graduation employment prospects, and the quality of educational research thanks to LA.

The difficulties stemmed from the necessity of optimizing the learning environment, ethical and privacy concerns, and a need for more relationships to learning science.

Ihantola et al. (2015) evaluated LA case studies focusing on computer science courses, looking at their purposes, methods, environments, topics, and assignments, data and gathering, and methods of analysis. The targets concerned the students, the software, and the classroom itself. Research methods such as case studies, exploratory analyses, controlled experiments, and surveys were used. They also observed that the majority of the study was carried out in the framework of a course,with the sample sizes ranging from 10 to 265,000, with the majority (64%) including 500 participants or fewer. Most of the research had participants carry out a series of programming exercises. Sixty or more percent of the automatic data collecting was employed in the research that kept track of the student's activities, and they used numerous techniques for analyzing the data, including descriptive and inferential statistics.

2.2 Conceptual and Theoretical Background

Social cognitive career theory (SCCT) is a useful paradigm for dissecting and comprehending the processes by which individuals choose a career route, form interests, and overcome setbacks in their professional development. In 1994, Robert W. Lent, Steven D. Brown, and Gail Hackett founded SCCT as an area of social cognitive theory, drawing inspiration from Albert Bandura's research. This hypothesisof cognitive and motivational processes has been researched in relation to a wide range of psychosocial outcomes, including educational success, positive health habits,and business expansion. Additionally, SCCT gives a theoretical framework for figuring out how people get interested in careers, decide on occupations, and find long-term success and satisfaction in those occupations (Lent & Brown, 1996; Niles & Harris-Bowlsbey, 2009). Different from other theories, SCCT investigates the various ways in which an individual may come to pick and remain in a certain vocation. The SCCT theory stands out from the crowd since it investigates not just one but several potential routes that lead to a person selecting and remaining in a given profession.

Retention and learning analytics

A higher rate of student retention is desired because, it is important to identify students who are at risk early so that they can receive the necessary learning supports and interventions. Predictive analytics is being used more frequently to guide these types of actions. A student's profile is constructed using these analytics by giving equal weight to demographic information, online engagement data , and an assessment of school grades) (Macfadyen, L.P et al. 2010). It is clear from a growing body of evidence that LA has the ability to create effective early alert systems to solvestudent retention issues (Wolff, A. et al., Dietz-Uhler, B. and J.E. Hurn, 2013). The field of learning analytics uses predictive modelling to provide a comprehensive overview of early alert systems (Jayaprakash et al., 2014). (Kahu 2013) Student engagement, which influences on proximal and distal outcomes from structural, pedagogical, and psychological contexts, is the construct upon which retention depends and from which it emerges. This way of thinking raises the prospect that problems with student retention could be fixed not at the time of students' departure but in the way that students interact with these preceding factors. Insight into the usage and influence of Learning Analytics in Bengalurun Higher Educational Institutions, as well as a deeper understanding of the factors affecting such use, are theprimary goals of this study.

Retention

In higher education, retention refers to the rate at which enrolled students either complete their original program of study at the same institution, switch to a different program, or drop out of school entirely (Woodfield, 2014).

Attainment

The percentage of young (15-24) and adults (25-64) with a bachelor's degree or above rose dramatically between 1990 and 2016. (Institute of Labour Market Information and Analysis, 2018). According to a report by Woodfield (2014), attainment is worried about the result, mainly whether or not students graduate from their degree course and what grade (i.e., classification) they get.

Employability:

Employability, as defined by Fugate et al. (2004), is "the capacity to recognize and exploit occupational opportunities." *Employment potential* is a trait that describes an individual's potential for gaining and maintaining gainful employment (Shahzad et al.,2020). There has been much focus on employability in higher education because of itsimportance in the job market and because of the shared goal of universities and individuals to increase the employability of graduates (Fugate et al., 2004). A few studies look at the essential contributions of LA at Bengaluru HEIs, even though LA applications are still in their infancy. (Wong, 2017; Tasir et al., 2016; Clow, 2012).

Achieving sustainable success in implementing LA requires strategic direction and effective leadership techniques. According to Rick (2013), objections may be decreased by recognizing conflicts that need to be fixed and planning for them at the outset of the LA modification process. Therefore, bringing about change and addressing issues is essential for institutions to change and utilize the LA tool and its advantages for students, staff, and other stakeholders (Tasir et al., 2016).

2.3 Hypothesis development Impact of Retention on Attainment

Educators, legislators, and parents are deeply divided over whether keeping pupils performing poorly in school is worthwhile. Proponents of keeping students from leaving school too early argue that doing so would send an unprepared student into the world. They contend that a child's readiness and sense of pride can benefit from being held back in elementary school to strengthen their foundation of basic skills. Some educators believe that children need to be held accountable for their academic performance in later grades by facing the possibility of retention if they do poorly (Frey, 2005).

It was initially thought that keeping students back would help them learn more, grow up faster, and strengthen their foundation of skills. Many scientists now perceive it as more of a poison than a treatment, and they cite an ever-expanding body of evidenceto back up this position (Alexander, 2002).

Compared to their peers, the academic performance of retained children does not improve after repeating a grade, and retention also considerably raises the risk that a kid will. Social promotion or grade retention will not help students catch up academically or keep them from dropping out. We need an approach that does not "wait for failure," not resort to kneejerk reactions that are more retributive than preventative. Even though it would be foolish to say that students should never be retained, educators must be conversant with the available literature on retention and its alternatives (Adelman & Taylor, 2006). To further our understanding of effective interventions, educational accountability systems allow teachers to develop and test new strategies with specific subsets of children. Evidence-based instruction, when used by teachers effectively and consistently, is the most promising method for improving student results across the board (Picklo & Christenson, 2005).

Impact of Attainment on Employability

Individuals with remarkable academic achievements are more likely to have a narrow focus, more extraordinary (unique) knowledge and skill in the topic, and hence are viewed as a suitable provision for those entering the workforce (Omar, NH, Manaf 2012). Individuals with high levels of academic accomplishment will be self- motivated to have higher employability by improving their prospective skills and knowledge, as stated by (Dacre, Pool, and Sewell 2007). The results of a study by Surridge (2009) reveal that people with low levels of education are more likely to hesitate when making important life decisions like picking a career path. This agrees with the findings of Omar, Bakar, and Mat Rashid (2012), who found that a lack of knowledge and skills negatively impacted job prospects.
Various variables can affect a graduate's capacity to find gainful employment, and these have been the subject of previous research. Employers look for recent graduates with strong communication skills, general knowledge, personality , computer and IT skills , realistic experience , and academic background (ABS). According to Paddi (2014), employers are actively seeking recent graduates with excellent interpersonal, analytical, and critical thinking abilities and computer literacy. Employers value practical knowledge, logic, desire to work, communication and IT abilities, managerial capabilities, and a positive attitude (Liyanage et al. (2016). Academic knowledge and the development of soft, practical, and technical skills were identified as the essential parts of getting a graduate ready for the workforce in a study (Ambepitiya 2016).

Impact of Retention" on Employability

Many students take on part-time jobs while studying, so those dedicated to assisting students (such as college and university administrators, professors, academic advisors,and personnel in student affairs) must learn how to best leverage this trend for studentengagement and learning. One of the few promising ways that only need a few resources is encouraging increased degrees of deep learning and goal realization through work experience. To paraphrase (McClellan et al., 2018, p. xiii) Furthermore, adding new students to an existing employment program requires littleto no additional funding. Gaining a higher retention rate benefits the institution's bottom line and the student's academic progress (Burnside et al., 2019).

If a school can keep its students for four years, that school will make as much money as if it had enrolled four new students who dropped out after a year, plus the cost of attracting new students who did not stick around (McClellan et al., 2018). According to Tinto's concept, students are more invested in their institutions when they have opportunities to bridge their academic and social lives from an early age (Berger et al., 2005). There is a correlation between making these pledges and increased retention rates. Using this framework, Tinto identifies three primary reasons why students drop out: difficulties in the classroom, problems in achieving professional or academic goals, and disinterest in the intellectual and social life of the institution (McClellan et al., 2018). Further, a student employment program on campus offers a nurturing setting where students can safely put their classroom knowledge into practice (Kuh, 2018). According to (McClellan et al., 2018), a student employee whose job is supported by the Federal Work-Study program is the only kind to whom the term "work-study" should apply. If we emphasize the importance of development, learning, and retention in the classroom, we can message students that they and we should view their position as a combination of labour and study.

Attainment mediates the relationship between Retention and Employability

The success of universities can be measured by their ability to keep their students enrolled. In order to keep students and secure future government funding, schools may decide to improve the quality of the services they provide. Investigates the factors that contribute to students' ability to remember what they've learned by looking at their immediate surroundings, including the effects of Learning analytics, friends and family, and academic performance. Previous research, such as those by Mahadzirah and Zainudin (2009), Peter, Hong, Gabriel, Mustafa, and Tan (2005), andothers, have shown that a company's image can have an effect on its students' loyalty (2010). The Association of American Colleges and Universities (2007) states that the achievement of a student can be gauged by their ability to achieve success in their chosen profession, in their personal lives, and in their communities.

Objectives:

1. To identify factors impacting Learning Analytics in Bengaluru HigherEducational Institutions.
2. To study the impact of Students Retention and Students Attainment onStudents Employability
3. To study the mediation effect of Students Attainment between StudentsRetention and Students Employability in Bengaluru HEIs.

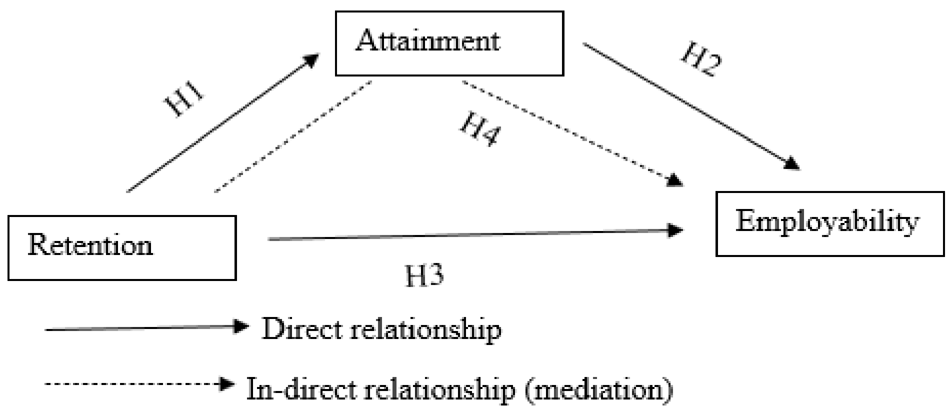


Figure 1: Conceptual framework of the study

Hypotheses:

H1: There is a significant impact of Retention on Attainment. H2: There is a significant impact of Attainment on Employability.H3: There is a significant impact of Retention" on Employability.
H4: Attainment mediates the relationship between Retention and Employability.

3. RESEARCH METHODOLOGY

Mixed methods convergent parallel design used for this research **(Creswell, 2015)**. The research population includes all Higher Educational Institutions (HEIs) in Bengaluru. There are two parts to this survey. The first section includes the sample's demographics, as shown in Table 1, and the second section includes the sample's responses to the questions, which participants rated on a 5-point Likert scale, where 1= strongly disagrees and 5 = strongly agrees. The respondents of the study are Chancellery, Dean, HOD, and Directors. A total of 485 questionnaires were delivered to Bengaluru public and private HEIs. Four hundred fifty respondents returned back the questionnaire. During the data screening process 13 questionnaires containing missing data or outliers were not included in the study. Thus, the final sample consistsof 437 usable questionnaires for further analysis.

3.1 The measuring instruments

The proposed model as shown in Figure 1, incorporates retention, attainment, andemployability. The measures for the independent, mediator and dependent variableswere selected based on exhaustive literature review on present research. The scalesfor retention were derived from the study of Woodfield (2014). Skewness and kurtosisvalues should be confined between ±1.50 as the acceptable limits. Thus, bothSkewness and kurtosis findings indicate that the responses in this study's dataset arenormally distributed (**Tabachnick and Fidell 2019)**. The attainment (mediator) was measured using four items adapted and finally, the student's employability (the dependent variable) items were adapted from Chen and Li, (2011) and Wang et al., (2022) study.

3.3 Technique of data analysis

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

The study's primary tools are the Statistical Package for the Social Sciences (SPSS) and AMOS version 22. The structure of a collection of measured data was first determined using exploratory factor analysis. EFA also aids in determining the construct validity of an instrument during its early development. Following the completion of the study's factors, the Confirmatory factor analysis (CFA) was used to determine whether the proposed scale was adequate for the investigation. The final step was to do Structural Equation Modelling (SEM), a multivariate technique that simultaneously analyses numerous regression equations to estimate the relationship between all of the study's variables. The model was tested along with mediationanalysis and results are discussed in following subsections.

4. Data analysis and Results:

4.1 Demographic Information:

Table 1: Demographic profile of the respondents

Measures	Items	Frequency	Percentage
Gender	Male	222	49.3%
	Female	228	50.7%
Age (years)	18-21	150	33.3%
	22-30	147	32.7%
	More than 31	153	34%
Ethnics	Bumiputera	150	33.3%
	Chinese	150	33.3%
	Indian	150	33.3%
Years	1st year	45	10%
	2nd year	168	37.3%
	3rd year	108	24%

	4^{th} year	129	28.7%
	Bachelor	147	32.7%
	Master	150	33.3%
	PhD	153	34%

Source: Primary survey

4.2 Exploratory Factor Analysis

The different factors impacting Learning Analytics in Bengaluru Higher Educational Institutions were extracted using exploratory factor analysis (EFA). Before conducting the analysis, the adequacy of sample was determined by the Kaiser–Meyer–Olkin (KMO) tests and the KMO statistic is 0.883, appropriately greater than the recommended cut off 0.70. This value confirmed that sample is sufficient for running factor analysis. Furthermore, the Bartlett test of sphericity also supports the adequacy as it was significant, at the 1% level of significance.

Principal Component Analysis (PCA) using the Varimax Rotation Method Kaiser wasused to analyse the 13 variables. For factor analysis, normalization is a necessary step. Items with factor loadings below 0.50 should be removed from consideration (Hair et al., 1996). All items have factor loading more than 0.50 so no items are excluded fromthe analysis. So, all 13 items are accepted. After using the factor selection criteria based on Eigen value above 1, three factors were extracted explaining the totalvariance of 82.064%, which indicated a good. Each component of the suggested instrument accounted for more than 60% of the total variance, indicating that the procedure was effective. Please refer to the table below for a summary of the PCA results.

In addition, the internal consistency of a scale or test can be evaluated using Cronbach's alpha to ensure that the measurements are reliable. This global assessment of a measure's dependability is represented by a coefficient with a value between 0 and 1. If all of the scale items are entirely independent from one another than $\alpha = 0$; and, In the event that the covariances among all of the variables are extremely high, then α will approach 1. A higher reliability score indicates a more trustworthy created scale. According to Nunnaly (1978), a coefficient of dependability of 0.7 is considered satisfactory.

Response consistency across three parameters is evaluated using Cronbach's alpha (Cronbach, 1951). Internal consistency can be evaluated using Cronbach's alpha, and a value above 0.70 (Nunnally, 1978) indicates that the questionnaire has reliability and can be used for further study.

Table 1: **KMO and Bartlett's Test**

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.883
Bartlett's Test of Sphericity	Approx. Chi-Square	5464.488
	df	78
	Sig.	.000

Table 2: Results of EFA and alpha values

Construct	Factor loadings	Eigen Value	% Variance	Cronbach's alpha
Retention		6.444	49.573	.958
RT1	.893			
RT2	.910			
RT3	.900			
RT4	.862			
RT5	.855			
Employability		2.359	18.148	0.921
ET1	.886			
ET2	.888			
ET3	.851			
ET4	.878			
Attainment		1.865	14.344	0.904
AT1	.862			
AT2	.898			
AT3	.884			
AT4	.739			

Source: Primary survey

4.3 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 findings, or both, canonical factor analysis (CFA) makes hypotheses about the organization among variables and then conducts statistical tests to see if they hold. Validity and reliability of the constructs were evaluated using CFA, and the model was created based on a priori subject matter. While developing the CFA model, we treated each concept separately as an exogenous variable.

4.3.1 Model fit

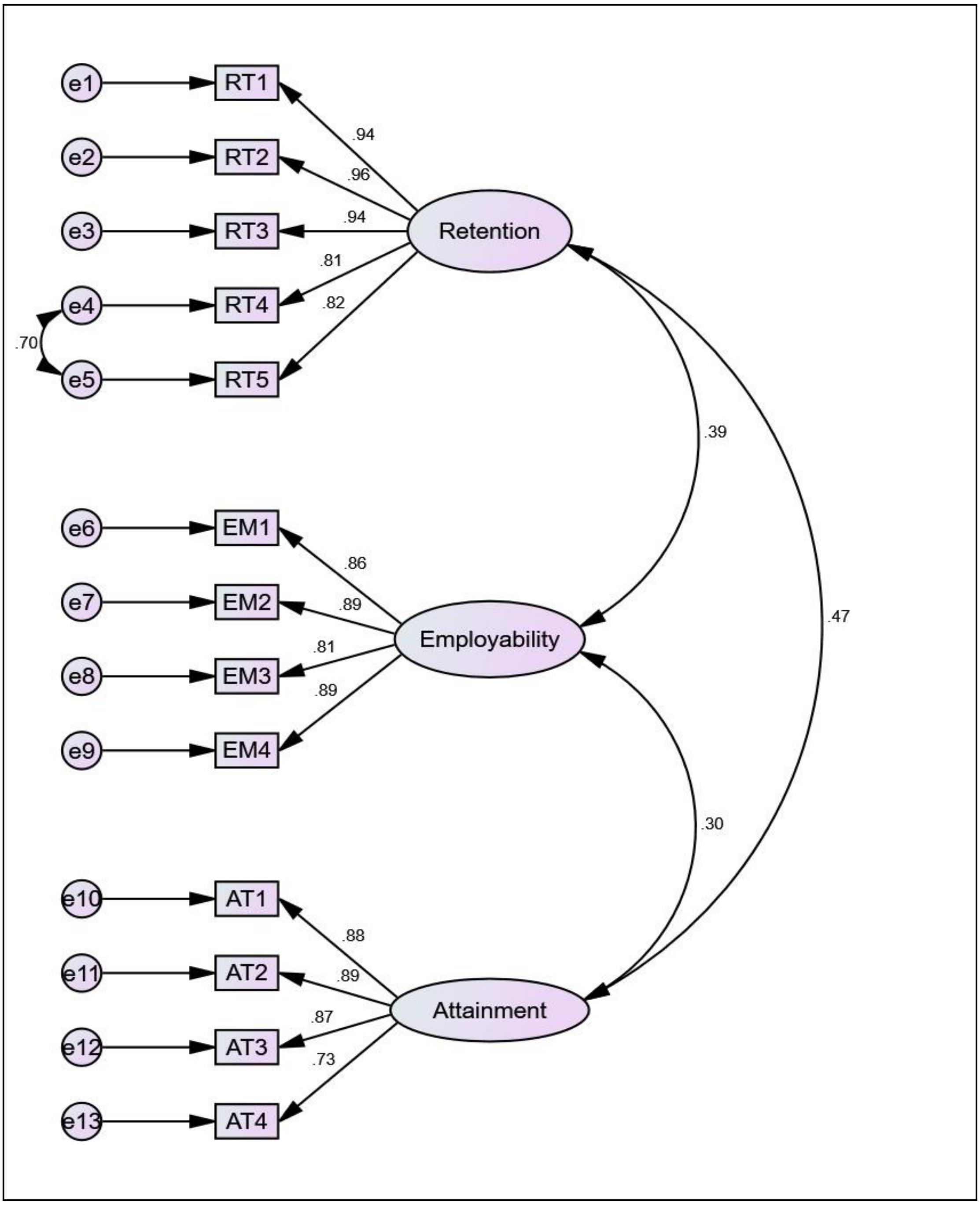
Table 3 displays the results of the overall fit statistics used in testing the conceptual model. The good indicators of fit statistics such as CFI, NFI,GFI & AGFI with the bad indicator RMSEA , all these measures are in the range that wouldbe associated with good fitness. These diagnostics suggest, model provides agood overall fit (Hair et al., 2010; Hu & Bentler P, 1999)

4.3.2 Reliability and validity

Composite reliability (CR) and average variance extracted (AVE) are used to evaluatethe convergent validity (CR). All AVE values are more than the threshold of 0.50, validating the measurement model's convergent validity, which gives a range of 0.608to 0.809. (Fornell and larcker, 1981). Additionally, the CR value of all the seven research constructs is above the threshold value of 0.7.

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

Figure 2: CFA model for the proposed scale



Source: Primary Survey

Table 3: Goodness of Fit indices in CFA model

Indices	**Abbreviation**	**Observedvalues**	**Recommendedcriteria**	**References**
Normed chi square	χ2/DF	2.769	1<χ2/df<3	Hair et al.,
Goodness-of-fit index	GFI	0.942	>0.90	(2010)
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 acceptablefit	
Tucker-Lewis's index	TLI	0.975	0<TLI<1	

Table 4: Composite Reliability, Convergent Validity & Discriminant Validity forScale 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

4.4 Hypotheses testing using SEM model

The study runs SEM analysis using maximum likelihood method to test the causal relationship between learning analytics factors. The impact of Retention asindependent variable (exogenous) on student employability as dependent variable (endogenous) were tested along with attainment as mediator between these two variables. The criteria for selection or rejection of research hypothesis based on critical ratio value of path above ±1.96 and p value less than 0.05 at 5% level of significance.

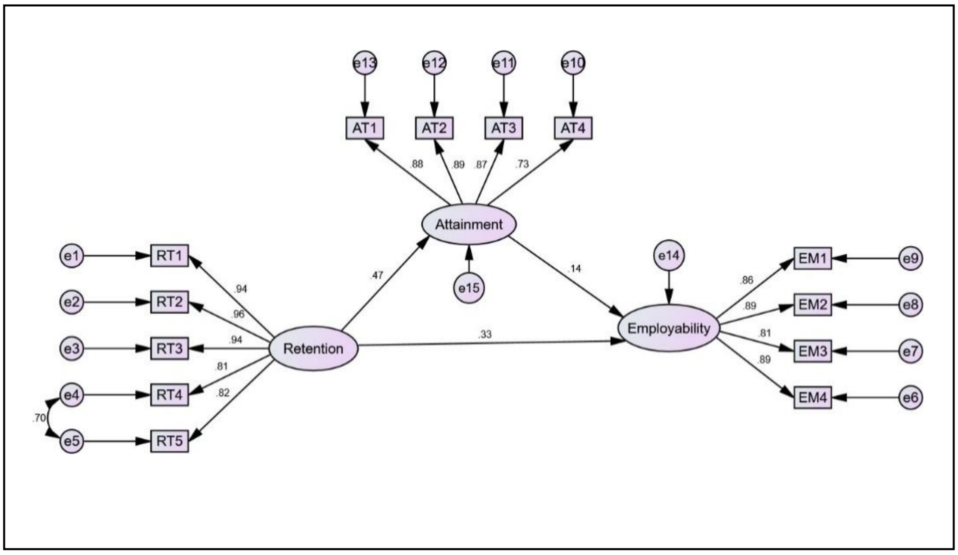
Table 5 displays the findings of the path analysis and hypothesis testing. The standardized path coefficient and the p-value for each association are displayed. By referring to Table 5 and Figure 3, it is concluded that the standardized path coefficient(β) of retention to attainment is positive and significant as β =0.473 with p=0.000. Since p value <0.05 and CR (9.307) >1.96, thus hypothesis H1 accepted.

The impact of attainment on employability of student is positive and significant having β = 0.142, CR = 2.553 and p =0.011 (p< 0.05), provided sufficient evidence to accept hypothesis H2. Similarly, retention positively influenced employability with β
= 0.327, p= 0.000. This relation is significant as p value less than 0.05, therefore hypothesis H3 was supported from this finding.

The coefficient of determination (R^2) value is 0.355, for attainment inferred 35.5% of variation in attainment is explained by retention. The two predictors of employability,
i.e. retention and attainment explained 42% of the total variance in students' employability.

The fit indices of the measurement model are CMIN/df =2.769; p =0.000, RMSEA = 0.068, CFI = 0.980, NFI = 0.969 and AGFI = 0.914. The results indicate that the structure model fits prediction and interpretation.

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



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 2,000 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 computed 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 effect is non-significant ($p > 0.05$), it implies full mediation.

The findings from table 6 revealed that Retention has a significant indirect effect on Employability through Attainment. We can conclude that Attainment is significantly mediating between Retention and Employability. Since both standardized direct and indirect paths have p value below 0.05, thus, it is confirmed that attainment **partially** mediates the relationship between Retention and Employability of the students. These findings support the acceptance of hypothesis H4.

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

Relationship	Standardized indirect effect	Standardized direct effect	Standardizedtotal effect	Results
Retention Attainment⟶ Employability ⟶	0.072 p = 0.033	0.348 p =0.002	0.420 p = 0.002	Partial mediation

Source; The authors

Discussion:

As learning analytics entails recording, examining, and reporting information related to the learner and learning environment, it becomes crucial to identify factors and their influence on learning analytics. The current study has explored retention, attainment, and employability as the critical factors that must be considered before applying Learning Analytics in Higher Educational Institutions. The research results confirmed that students' employability is significantly influenced by retention and attainment.

The positive influence of retention on employability suggested that students with a higher degree can save money, be healthier, and have longer life expectancies. This finding is in line with the study of Habley et al. (2012). Therefore, higher institutions should understand retention and frame strategies accordingly.

The results also revealed that attainment significantly and positively impacts students'employability in higher education. This finding is consistent with previous studies(Woodfield, 2014). The University should provide Virtual Learning Environmentplatforms and use social media to strengthen student and faculty relationships toincrease students' attainment. Once students are equipped with the required skills,they are ready to enter the workforce, stay in a place of work, and move to other jobs. As evidenced in the results, attainment plays a partial mediator between the retentionand employability of students in higher education institutions, confirming that studentdesire to continue or to be in higher education leads to an increase in theiremployability. However, it is influenced by skills, motivation, personal attributes etc.It is required for institutions to accommodate digital skills and industry-based projectsto provide hands-on experience to students and simultaneously advisable for studentsto participate in professional and certified courses to increase digital skills.

Institutions were viewed as the LA drivers, with retention conceived as a (far) activitythat was directly linked to antecedent teaching, learning, and student experience characteristics. On the other hand, there is a narrower focus on a single institutional issue when LA is used in a formal setting (e.g., student retention and attainment). However, little attention was paid to the potential of analytics to better understand the educational experience of students and direct the development of course and programme curricula. In this case, the many ways in which LA can be put to use were overshadowed by the emphasis placed on activities designed to keep students in the classroom (such as discourse analytics, social learning analytics, and self-regulated learning). If the data gathered through LA is to provide meaningful and pertinent signals for teachers to be able to take the appropriate course of action, as Romero (2019) proposes, teachers must be involved in the process from the conceptualization of methods for data collecting through its analysis. Human-cantered Learning Analytics are mentioned by Buckingham-Shaum et al. (2019). This method takes the shape of a methodical plan to involve academics from across a university with LA anddevelop their skills through cooperative training programs that promote action research.

Conclusion

Evaluating the efficacy of pedagogies and instructional designs is made easier with the aid of learning analytics, which can also aid in keeping a close eye on students' progress, predicting their performance, spotting problematic patterns of behavior and emotions in the classroom, and identifying those most in need of immediate attention. As a bonus, it can give students valuable information about their unique learning styles and habits, allowing them to better tailor their education to their individual needs and interests while encouraging self-reflection and growth. Findings also showed that retention and success in the classroom significantly impacted students' capacity to seek employment after the academy.

Limitation:

Academics in Bengaluru were surveyed for their thoughts on the matter, and their responses were analysed without regard to the academic fields in which they specialize in teaching. However, this restriction does not lessen the significance of thefindings and can be seen as a suggestion for further study. In order to see how research has changed over time, it is possible to undertake a longitudinal study that compares literature from different years. Combining the expanded approaches with experimental and simulation methodology to build standardized tools would allow fora cross-national study comparing the implementation in various nations.

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