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Online Learning for Enhancing Employability Skills in Higher Education Students: The Mediating Role Of Learning Analytics

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***Abstract* – Globally, with the recent technological advancement and innovative capabilities, Higher education institutions (HEI) are adopting information technology tools for teaching in online environments through virtual classroom platforms. Further, the administration of HEI is majorly concerned with students' employability skills and is always willing to empower students to achieve their career goals. The study explores the online e-learning tools like learning analytics and examine their impact on the employability skills of students of higher educational institutions for sustainable development.**

The paper investigates the mediation effect of learning analytics in influencing the online learning usefulness, and knowledge on the employability skills of the students. The study has used PLS-SEM approach to analyze the responses collected from 172 undergraduate students across universities of Delhi-NCR to test the hypothesis. The results confirm a positive and significant mediation of learning analytics in the relationship of e-learning usefulness and knowledge in achieving employability skills.

***Keywords* – Learning analytics, higher education, employability skills, partial least squares, mediation**

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1. Introduction

Higher Education Institutions (HEI) often experience difficulties in covering course content in a timely manner along with ensuring skills acquisition in a dynamic and competitive environment of technology and infrastructure [1], [2]. In addition, institutions are also under pressure to [increase students' number in specific courses and disciplines by incorporating workplace attributes for graduates in the higher education system. This would ensure that the learning environment can meet the national and global challenges and requirements of employability skills. Furthermore, the diverse stakeholders eagerly expect HEI to adopt appropriate measures at the earliest to handle the declining government funding [3],[4] and increase operational costs [5], [6].

Using technology to address these concerns has widely been accepted and mentioned in the literature [7],[8]. Information technology tools adopted in the classroom offer more flexible environment to review and access content in a blended environment [9]. The web-based application tools in the learning environment are often termed online learning or e-learning like Moodle or Web CT [10]. The available hyperlinks to the web page connect to other parts of the web, enabling access to a vast amount of information related to the course contents [11], [12].

Online learning tools and courses provide a wide range of skills and knowledge for the learners attending live classes [13]. Mobile devices are famous for web-based learning nowadays. They have tremendously increased the use of e-learning materials, specifically among the college students falling between 18-29 years of age [8]. The use of online facility in learning is rapidly increasing, but it has also led to a change in lecture composition, student attendance, and interaction among students.

There is a need to effectively handle the rapid changes in teaching-learning pedagogy and have overall development in the present scenario of rapid globalization. Data and learning analytics can play a significant role in existing conventional education and understanding the need for an online learning environment [14]. It will enable institutions to achieve their goal of shaping students' sustainability-specific employability skills and ensure they can face the rapid pace of change in a technological and learning environment within and outside the system.

2. Literature Review

Internet education has been dominating and it is now one of the most desirable among students nowadays. Higher educational institutions have made significant progress in spreading virtual classrooms platform and learning environments [15], [16]. Virtual classes and faculties do not mean that "classrooms without walls" willfully replace the conventional educational system and traditional faculties. They will continue to be significant but need to change with newly available technology and fulfill the requirements of contemporary education [17]. This will keep attracting students who prefer learning with conventional methods. Consequently, a virtual classroom environment will positively influence traditional faculties to innovate as well [18].

The E-learning process and the innovative capabilities in digital technology have increased the accessibility of online learning and have crossed restrictions of limited workplace. It has offered a conducive environment for the outcome based learning, usually mediated by integrating new technology and tools [19]. The E-learning acceptance model (ELAM) provides four factors of e-learning acceptance – (i) Performance expectancy, which takes into account beliefs relating to the professed flexibility, interactivity, and usefulness, (ii) Effort expectancy, which is established on the beliefs about convenience and efficacy (iii) Social influence, concerning the subjective norm and (iv) facilitating conditions.

Many authors have identified essential factors in adopting e-learning, which can be measured by behavioral intention to use the technology [20]. Teaching strategies in online courses can be identified as (i) Auditory learners, (ii) Visual learners, (iii) Kinaesthetic learners, (iv) Read/write learners. The aim of virtual learning can be attained by providing instructions in a specified order that matches the specific learning outcome desired for assessment and evaluation [21], [22]. Therefore, it is essential to critically analyze the relationship between theories of learning and concepts of learning outcomes (LOs) to meet the global standards of higher education. This article contributes to the Learning outcome through analytics which serves as an important tool for faculty to improve their teaching methods and also for the purpose of formulation of policies for Higher Education Institutions.

2.1. Big Data in Learning Outcomes

Big Data is an emerging field of research for learning analytics that can convert management decision-making theory into practice [23], [24]. It presents the learning outcomes framework utilizing the vast array of data and gives a new dimension to higher education learning. Research has contributed to technology and the growing need for analytics in higher education, particularly interdisciplinary research, creating loops in education, statistics, mathematics, and information technology [23].

Big Data in higher education includes database management systems to capture and store longitudinal data on students' transactions and teaching-learning activities. For example, while taking the e-learning courses and interaction, students generate a trail of data that can uncover their behavior, intentions, social connections, and objectives.

Furthermore, Big Data Analytics also covers an assessment system that could be useful to examine the learner for his assignment submission, onboard discussions, blog entries, or wiki activity [25], which could produce a vast number of transactions per student per course. All the data is gathered on a factual or near real-time basis and analyzed to suggest further learning and teaching activities. [26] mentioned that "learning analytics is a foundational tool for informed change in education" and give evidence to understand and make informed rather than intuitive decisions.

One of the major concerns for higher education institutions (HEI) is the employability rate of students, and they are curious to take steps for the betterment of the student community. Authors advocated using various classification techniques of data mining and the employability prediction of students in HEI [26].

Better employment can be generated by providing the appropriate knowledge and skills through higher education. Usually, it is observed that college graduates face significant competition from experienced employees [27].

Big Data analysis signifies evaluating and interpreting a wide variety of administrative and operational data collected through practices that intend to assess the performance and progress of an institution so that future implementation and functioning can be predicted and identify possible issues pertaining to research, teaching, learning, and academic programming, [28], [29].

2.2. Learning Analytics and Employability Skills

Learning analytics has recently emerged as a promising research area where data is collected, assessed, and interpreted to bring into light new dimensions to each user's learning process. With the technological advancement in the current time, various systems of learning management and digital technologies can produce and demonstrate data visualizations in a way that may be considered as 'learning analytics' [16], [30]. Learning analytics allows gathering and processing data as people engage in learning to enhance learning and teaching.

Nowadays, higher education institutions use a blended approach for teaching where learning is enhanced with tailor-made/user-friendly e-resources and online platforms. Experts in educational data mining and learning modeling suggest numerous tactics to track how a student is reacting during the learning process and record actions like time devoted to a page, the number of clicks, etc. This has led to accessible information to draw attention to the learners' litheness and retention of concepts. Moreover, the growing repository created through the collated data on the learners' behavior enables the data mining experts to further research and new conclusions.

Learning analytics is the process of gathering, measuring, investigating, and reporting data related to learners and their environment. It aims to understand and improve learning by arugmenting the environments where learning occurs [24]. On a broader sense, the techniques and methods usually used in learning analytics focuses on evaluating educational and institutional data, improvisation of processes and workflows, and developing organizational effectiveness, thereby enabling a user to have more customized learning [31], [32].

For skillful professionals, intended learning outcomes of educational programs and the students' progression are keys to employability [33]. Learning Analytics instills data analytics and teamwork skills in learners. It studies the process of learning by gathering and evaluating data related to education and regularly assessing it for adaptive learning outcomes [34].

Learning analytics as a technique is majorly used at the institutional level for the teaching and learning process and is essentially concerned with increasing the success rate with which helps the students to learn and understand more efficiently [10]. [35] conducted an early study that examined and demonstrated improvement in students' learning outcomes and learning support and teaching. However, the suggested potential of learning analytics in student skills could not shift the higher education practice in the past few years.

This study examines the mediating role of learning analytics in identifying online learning's impact concerning skills, assessment, monitoring, and development on the students' employability skills.

3. Research Methodology

3.1. Model Framework

Figure 1 displays the proposed model of the study. The model shows E-learning usefulness, knowledge and training skills on students' employability skills. The model also evaluates the indirect effect of learning analytics in explaining the relationship between e-learning usefulness, training skills, and familiarity with students' employability skills.

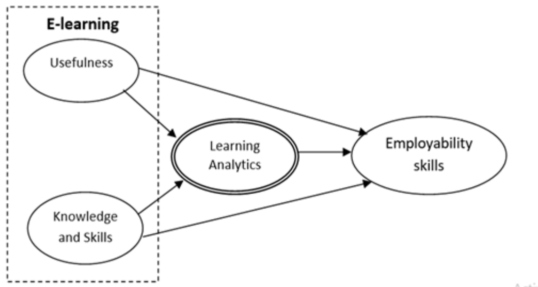

Figure 1. Research Model

3.2. Hypotheses Development

Although it is difficult to manage the enormous data, smarter technologies and learning analytics enable higher educational institutes to teach employability skills to students. The learning analytics technique regularly assesses adaptive learning outcomes by collecting and analysing the data related to learning [34]. Thus, skillful professionals intended learning outcomes of educational programs, and assessing the students' progression is the key for the students' employability [28], [33].

H$_1$: Learning Analytics positively affects Students' employability skills

The rapid changes in the online learning process have shown a new direction the research in teaching-learning pedagogy beyond the workplace boundaries. It has offered event-based and outcome-based learning, usually mediated by integrating new technology and ICT tools [18]. The gap between skills and employment opportunities and the burden of training on the employers can be addressed meaningfully through the e-learning process [35].

Employability skills relate to e-learning to gain the skills and personal attributes that enable a student to achieve a successful career [36]. Earlier studies have studied the relationship of employability skills, e-learning knowledge, and skills and at the same time develop their careers during social and technological change [37], [38].

H_{21}: E-learning usefulness positively influences students' employability skills.

H_{22}: E-learning knowledge and skills positively influence students' employability skills.

With the blended approach adopted by higher education institutions, learning is increasingly happening through online platforms and utilities. Learning analytics plays a pivotal role in education amidst the big data revolution explosion as an educational data mining tool [16], [39]. Early research has investigated the role of learning analytics in online learning to promote self-regulated learning and improving the abilities of time management skills [40], literacy skills [41], enhance virtual learning [17]. This study fosters the need to study the mediating role in the relationship of e-learning with students' employability skills.

H_{31}: Learning Analytics has a mediation role in the relationship between E-learning usefulness and students' employability skills.

H_{32}: Learning Analytics has a mediation role in the relationship between E-learning knowledge and skills with students' employability skills.

4. Methodology

4.1. Survey

The study has used a purposive sampling (non-probability) approach to collect the data for the sample survey. A structured questionnaire has been administered to gather the research data. The constructs of E-learning usefulness, knowledge, learning analytics, employability skills constitute 22 question items in total are shown in Table I.

A five-point Likert scale has been used; the respondent's strong agreement is indicated by 5 and strong disagreement is indicated by 1. Respondents were suggested to assess opinion on the items given in the questionnaire according to the Likert scale. It also envelops questions relating to the demographic nature of the individuals.

Table 1. Construct and Items

Item Number	Item description
A	**E-learning Usefulness**
EU1	E-learning is accessible in remote locations
EU2	E-learning helps you in professional development
EU3	E-learning facilitates interactive collaboration
EU4	E-learning improves the critical and logical thinking
EU5	E-learning can be applied in different type of occupations
EU6	E-learning makes the best use of time
B	**Learning Analytics**
LA1	LA can help in analyzing real time data
LA2	LA can help in analyzing feedback and relationships
LA3	LA provides advanced analytical algorithms and data visualization
LA4	LA provides efficient and economical data solutions
LA5	LA provides high speed data mining and streaming processes
C	**E-learning knowledge & skills**
EKS1	E-learning offers network-enabled transfer of skills and knowledge
EKS2	E-learning offers a wide range of efficient solution
EKS3	E-learning offers skill based required knowledge
EKS4	E-learning helps manage the work effectively and efficiently
EKS5	E-learning helps to skill based practical trainings.
D	**Employability skills in students**
ES1	Personality development and communication skills
ES2	Basic quantitative skills
ES3	Time management skills
ES4	Presentation skills
ES5	Information technology skills
ES6	Scheduling, Planning, and management of a project

4.2. Data Collection

Respondents for the survey were 185 university students in a three-year undergraduate program from any discipline from Universities in India's Delhi-National Capital Region (NCR). During the survey, 172 valid responses were received from the students taking skill-based online courses. The resulting closing number of useful questionnaires was 172. Of the sample, 102 (55.1 percent) were male, and 70 (46.9 percent) were female students. The sample size of 100-150 respondents is appropriate in achieving the consistent results of the partial least squares approach (PLS-SEM) [42].

4.3. Construct Validity and Reliability

Table II shows the outcome of the reliability analysis and tests of convergent validity. The factor loading of all indicators onto their intended constructs was found to be greater than 0.6. We have removed one of the indicator that show the factor loadings less than 0.6 to confirm the uni-dimensionality of the constructs, ensuring the validity of the measurement model. The Cronbach's coefficient alpha is used to test the internal uniformity of the constructs. All latent variables in this study show value of Cronbach's alpha coefficient greater than 0.75, which indicates a high internal consistency in the indicators [43].

Table II shows the results of factor loadings, Cronbach's Alpha, Composite reliability, and AVE estimates. To find pieces of evidence for convergent validity, the study has computed average variance extracted (AVE) for all the latent variables. AVE > 0.05 confirms the convergent validity as suggested by [44], supporting evidence for convergent validity.

Table III demonstrates the Discriminant validity with a correlation matrix which presents the AVE of each latent variable with the squared correlations. All constructs indicate valid results to confirm the discriminant validity, the AVE was higher than the squared correlation [43], [44]. In the case of e-learning skills and the learning analytics construct, there is a small difference of around 0.066, where the diagonal value 0.765 is lower than the correlation coefficient (off-diagonal) between the two constructs, which is 0.831. However, this difference is not much and can be ignored [45] and supports the Discriminant validity between the constructs.

Table 2. Reliability coefficient and tests of convergent validity

Construct	Loadings	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
A: E-learning Usefulness				
EU1	**0.877**	**0.909**	**0.930**	**0.691**
EU2	**0.874**			
EU3	**0.888**			
EU4	**0.825**			
EU5	**0.841**			
EU6	**0.662**			
B: Learning Analytics				
LA1	**0.647**	**0.819**	**0.874**	**0.586**
LA2	**0.808**			
LA3	**0.635**			
LA4	**0.840**			
LA5	**0.865**			
C: E-learning knowledge and skills				
EKS1	**0.807**	**0.789**	**0.855**	**0.543**
EKS2	**0.772**			
EKS3	**0.667**			
EKS4	**0.752**			
EKS5	**0.677**			
D: Employability Skills				
ES1	**0.827**	**0.811**	**.870**	**0.541**
ES2	**0.488**			
ES3	**0.797**			
ES4	**0.895**			
ES5	**0.465**			
ES6	**0.820**			

Table 3. Correlation Matrix for the assessment of Discriminant Validity

	E-learning Usefulness	Learning Analytics	E-learning Skills & Knowledge	Students' Employability Skills
E-learning Usefulness	**0.831**			
Learning Analytics	0.623	**0.765**		
E-learning knowledge & Skills	0.614	0.831	**0.737**	
Employability Skills	0.622	0.696	0.660	**0.735**

5. Results

The study has used structural equation modeling (SEM) technique to examine the relationships. We have administered SmartPLS version 3.2.8 to carry out the analysis. All relations between the constructs have been examined. The first direct relation in the SEM model between e-learning usefulness (exogenous variable) and employability skills (endogenous variable) has been estimated. The second direct relation has been examined to see the influence of learning analytics on the employability skills of the students of higher educational institutions (endogenous variable). The third direct relation in the model has been examined between e-learning skills and the employability skills of the students. The mediating effects of learning analytics in both relations have been evaluated in the model.

SEM has become the most popular tool to examine the complex, interrelated structure between the variables [46]. SEM analysis is processed in two phases viz measurement model to examine the constructs validity and the structural model to examine the relations. The present study has used the non-parametric Partial Least Squares (PLS) technique developed by Wold (1981) for the SEM analysis. PLS-SEM competently takes care of the formative and reflective indicators in contrast to other available techniques of SEM. As PLS is a non-parametric approach, there is no assumption of multivariate normality, which is an advantage of using PLS over OLS. Further, PLS has no sample size limitations like the other SEM techniques [47], [48].

We begin with analyzing the impact of learning analytics on employability skills of the students of HEI. The estimated coefficient represented by β of learning analytics to employability skills equals 0.372 and is found significant at 0.1% level of significance. Hence, H1 was supported, indicating a significant positive influence of learning analytics on the employability skills of the students in the Delhi-NCR region.

The bootstrapping re-sampling method was used to check the mediating effect and the other hypotheses [49], [50]. The direct impact of e-learning usefulness on students' employability skills with the existence of learning analytics (the mediating variable) was found significant ($\beta=0.280$, $p<0.001$), suggesting the possibility of partial mediation. The bootstrapping results exhibited that the uniform indirect effect of e-learning usefulness to employability skills through learning analytics was 0.332, significant at $p<0.001$. Thus, it indicates that learning analytics partially mediates the relationship between e-learning usefulness and students' employability skills.

Further, the direct effect of e-learning skills and knowledge on students' employability skills due to the existence of learning analytics (the mediating variable) was found insignificant ($\beta=0.180$, $p>0.05$), indicating the possibility of full mediation. The outcome of bootstrapping has indicated that the standardized indirect effect of e-learning skills and knowledge to employability skills through learning analytics was 0.365, significant at $p<0.001$. Thus it, indicates that learning analytics wholly mediates the relationship between e-learning skills and students' employability skills.

Table 4. Results of Structural Model

Hypothesis	**Path (Direct Effects)**	Slope Coefficient	t Statistics	P Values	Results
H1	Learning Analytics -> Students' Employability Skills	0.372	4.529	0.000	**Significant**
H21	E-learning Usefulness -> Students' Employability Skills	0.280	3.919	0.000	**Significant**
H22	E-learning knowledge & skills -> Students' Employability Skills	0.180	1.664	0.097	**Insignificant**
Path (Indirect Effects: Mediation Model)					
H31	E-learning Usefulness ->Learning Analytics -> Students' Employability Skills	0.174	3.454	0.001	**Significant (Partial Mediation)**
H32	E-learning knowledge & skills ->Learning Analytics -> Students' Employability Skills	0.332	3.635	0.000	**Significant (Full Mediation)**

6. Discussion and Conclusions

The study develops a structural model that estimates the relationship between e-learning usefulness, skills, and knowledge with the employability skills of the students of HEI. In addition, learning analytics was employed to study the mediating role in the relationship. The results support all hypotheses of direct effects and estimate a significant positive influence of e-learning usefulness and learning analytics on the students' employability skills. It has also been noted that learning analytics partially mediates the relationship between the two. Further, the mediating role of learning analytics was found significant (full mediation) in explaining the relationship between e-learning skills and students' employability skills among the higher educational institutions of the Delhi NCR region in India.

The findings support the influence of e-learning practices in students' acquiring employability skills [26], [35]. Furthermore, the results are in harmony with the prior research work signifying that e-learning skills in the presence of learning analytics may lead to achieving career goals and improving employability skills [9], [10], [16].

Learning analytics has fully mediated the relationship between e-learning skills and the students' employability skills. This is because learning analytics allows for regular feedback and monitoring of the student-instructor interaction during e-learning skills. Besides, text-based asynchronous communication and recorded lectures can provide students with a self-paced learning experience.

In the current scenario, the rapid pace of technology change has compelled corporates to strive and secure competent, skilled labor, intending to cope with the advanced work processes and global innovations. The skill set and proficiency acquired by the graduates during the higher education are compared with the employability rates by various stakeholders like businesses, policy-makers, and the government, keeping the nation's prosperity in the broader frame [51]. The outcome of the present study recommends higher education institutions to adopt learning analytics to track student behavior to develop employability capabilities, and competencies among graduates.

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