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A detailed survey regarding the usage of different ICT technology modes adopted by higher education institutions

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ABSTRACT

Information and communication technologies (ICTs) in all aspects of life have become the tools that are present everywhere and in a ubiquitous manner. Over the last twenty to thirty years, it has been noticed that the application of ICT has significantly changed the procedures and courses of almost all the higher education institutions. The higher education field is a highly socially-focused practice and providing quality education is traditionally been linked with the efficient teacher and their capacity for a high level of one-on-one contact with students. The use of ICT in higher education allows for more student-centered learning settings. Due to the reason that the world is quickly developing into a digital place with a huge level of digital information, however, the role of ICT in higher education is becoming increasingly significant and will persistently to grow and evolve in the 21st century. The application of ICT in the teaching and learning process, as well as its effective usage in higher education, depends on a variety of tools and techniques. In this paper, a detailed analysis of various modes adopted by the institutions of higher education is made.

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1. INTRODUCTION

The technical progress of the modern world and the speedy expansion of social networks changed the course of higher education significantly. Whether the society and its educational sphere will succeed in general depends nowadays on the understanding of the direction of the strategic development of education by all participants throughout the learning system. Information and communication technologie (ICT) has long been an instrument of support in the higher education field. The application of technology in educational assessment started in the 1920s when Sidney L. Presses designed an automatic testing machine. Besides, the schools started to employ standardized evaluation and automatic scoring technology at the same time, which helped to make large-scale testing suitable, expedient, and cost-effective.

The number of internet projects today demands students to remain in touch through electronic mail or mailing lists or other newsgroups with students of other states of India or countries. The internet should also be an essential part of an integrated teaching system in higher education. It should be seen as a tool that supports and increases the learning and not by itself as a means. The April 1997 global strategy poll depicts that this is the only mean by which the internet adds value and quality to the learning process at the higher education level. Teaching and learning by employing the internet by itself do not lead to the attainment of curriculum objectives, because the part of supporting in the preparation of classes, a good knowledge of the

Internet allows helping students in their class activities relating to the Internet. Students can employ the Internet to join a discussion group, subscribe to a newsgroup, take lessons and keep in touch with professional colleagues, among others. At the institutional level, there are a number of ICT tools that have continuously been employed as discussed in:

– DIKSHA-Digital infrastructure for knowledge sharing: It has been formally started by the vice president of India on 5th September 2017. It is basically a national teacher platform that is presently being employed by both teachers and students across the country to provide distance education. It has the following features shows in Table 1.

Table 1. Digital infrastructure for knowledge sharing

QR Code	Language	Location-Based	Class-Based
After scanning the QR code, teachers and students can access the National Digital Infrastructure. The portal will present you with recommendations and study topics after you scan the code.	The following languages are supported by the portal: • Hindi • Marathi • English • Tamil • Telugu It comprises 18 languages.	The portal would first inquire as to which location you are a part of. For instance, you can decide between Delhi and Mumbai. Sub-location may also be requested.	It requires the user to select the class for which access to the study materials is necessary.

While placing teachers at the forefront, Diksha has an impact on already highly scalable and flexible digital infrastructures. It intends to offer teacher training programs, such as instruction on continuous and comprehensive evaluation (CCE) and learning outcomes. Diksha can be integrated into state government organizations' educational programs as well as private organizations' projects.

2. LITERATURE SURVEY

Muthuprasad *et al.* [1] have worked on during the COVID-19 pandemic in India, students' perceptions and preferences for online education. They have worked on an online survey consisting of 307 students. According to the findings, the majority of responders (70%) are willing to use online classes to handle the curriculum throughout the pandemic. The majority of pupils preferred to learn online using their smartphones.

Mishra *et al.* [2] have worked during the COVID-19 pandemic's shutdown period, on online teaching and learning in higher education. They have worked on a dataset consisting of a total of 78 faculty members and 260 students who took part in a descriptive survey to analyze their attitudes about online teaching and learning. Age, gender, and job title of teachers. The author has to work on a larger dataset for better results.

Paul and Jefferson [3] have worked from 2009 through 2016, and a comparison of student performance in an online vs. face-to-face environmental science course was conducted. They have worked on 548 students, 401 traditional students, and 147 online students each receiving a score. As a result, there is no substantial difference in student performance between online and face-to-face (F2F) students.

Gopal *et al.* [4] have worked on during the COVID 19 epidemic, and the impact of online classes on student happiness and performance. They have worked on data acquired from 544 respondents who were studying business management via an online survey. The findings suggest that four independent elements included in the study, namely teacher quality, course design, fast feedback, and student expectation, have a favourable impact on students' satisfaction, which in turn has a beneficial impact on students' performance.

Spitzer and Musslick [5] have worked on During the school closures caused by the COVID-19 epidemic, the academic achievement of K-12 children in an online learning environment for mathematics improved. They have worked before and during the closure, over 2,500 K-12 students computed over 124,000 mathematics problem sets. According to the findings, students' performance improved during the 2020 school closure compared to the previous year.

Yawson and Yamoah [6] have worked on a multi-generational cohort perspective on the satisfaction essentials of e-learning in higher education. They have worked on a dataset taken from an online learning management system (Moodle) which consists of 611 students. The findings show that contextualizing online education based on the cohort composition of multigenerational students could be one technique for improving student learning experience and satisfaction.

Martin *et al.* [7] have worked on importance, competence, and motivation in the use of current digital technologies by higher education faculty. They have worked on a total of 247 professors in the United

States replied to an online survey. The use of a learning management system was considered the most important and competent by faculty as a result.

Kaewsaiha and Chanchalor [8] have worked on factors influencing learning management system adoption in higher education. They have worked on a dataset taken from higher education institutes that have 584 students and 42 teachers from various disciplines. According to the findings, perceived resources (within the information system idea), work relevance, and subjective norms were all strong predictors of learning management system (LMS) utilization. Chiu [9] has worked on self-determination theory (SDT) is being used to explain student engagement in online learning during the COVID-19 epidemic. The author using the dataset consists of within 6 weeks of participating in online learning, 1201 grade 8 and 9 students completed pre-and post-questionnaires. The findings revealed that digital support strategies met students' requirements better, that all of the demands were predictors of engagement, and that relatedness support was crucial.

Mamun *et al*. [10] have worked on instructional design for self-directed and inquiry-based learning settings using scaffolded online learning modules. The author used a small sample size of 30 students is used in this investigation. The combined data were analyzed to see how effective the scaffolding was at each stage of the Paratheo-Anametamystikhood of Eris Esoteric (POEE) method and in terms of student progress through the modules.

Dumford and Miller [11] have worked on exploring the benefits and drawbacks of online learning in higher education for student engagement. They have worked on a series of ordinary least squares regression models that were used to examine the data. For both first-year students and seniors, the findings revealed multiple significant correlations between taking online courses and student involvement. Students who took a higher number of online courses were more likely to use quantitative reasoning.

Pardo *et al*. [12] have worked to predict academic performance, researchers combined university students' self-regulated learning indicators and engagement with online learning events. They have worked on a case study in a 145-student course. The findings suggest that using a combination of self-report and observed data to achieve a more comprehensive knowledge of effective university student learning could be beneficial.

Mastan *et al*. [13] have worked on a systematic literature review for the evaluation of a distance learning system (e-learning). They have worked on ScienceDirect, ACM, and Scopus are three major databases. In the end, 38 articles were published between 2016 and 2021. Platform, evaluation model, evaluation, model, approach, problem, trend, and challenge were discovered to be seven criteria in this statutory liquidity ratio (SLR). These seven criteria can be used to guide future e-learning research. As a result, this study gives information on criteria that might be employed in future e-learning research as well as an overview of the current state of the field.

Yeung *et al*. [14] have worked on COVID-19: challenges, strategies, and support: a thematic analysis of higher education students' perceptions of online learning in Hong Kong. They have worked on dataset consisting of 145 students. According to the findings, socioeconomic constraints may have hampered students' online learning by limiting their study environment and access to equipment.

Comparing sequential minimal optimization algorithm vs. logistic regression for predicting student academic performance is a project by engineer Bhutto *et al*. [15]. On Kalboard 360, which has 500 records and 16 unique properties, they have worked. The accuracy obtained is higher with sequential minimal optimization (79%) than with logistic regression (73%) K-means and unsupervised clustering technique have been developed by Martnez *et al*. [16] to measure the impact of behavioral and personality factors on academic performance of higher education students. They worked with a dataset of 153 first-year college students. This model has an 80% accuracy rate. For analyses of the effect of AI in online learning. On artificial intelligence, online learning, and learning organization for analyses of the impact of AI in online learning during COVID-19.

Alshehhi *et al*. [17] have worked. They have worked on datasets from academic references and develop a framework for data collecting and analysis at COVID-19. The results demonstrate that artificial intelligence produces effective outcomes. In order to analyze the impact of students' interactions with learning dashboards on academic achievement, Kokoc and Altun [18] have developed a prescriptive learning strategy that uses an e-learning environment in contrast to artificial neural network algorithms. The dataset they worked on included 126 students who signed up for the 12-week course. The outcome of the presented model demonstrates that algorithms using artificial neural networks are the most accurate in predicting academic success. In order to improve student performance in online learning at the end.

Aydodu [19] has worked on deep learning and artificial neural network (ANN). They have dealt with 3518 university students. This model is 80.47 percent accurate. Convolution neural network (CNN) and Navies Bayes classifier have been developed by Bhagavan *et al.* [20] for interaction and presence in online student learning. They worked using a dataset consisting of 35,887 photos of facial expression recognition and 12,271 real-world photographs of emotive faces (RAF) (FER2013). This model is 93% accurate. LMS and predictive models have been developed by Conijnet *et al*. [21] to analyze student performance from LMS data. With 4989 students, they have worked on 17 mixed courses. Finally, the outcome displays the LMS data's regression analysis. They are accessible every week to assess whether early action is likely. Input-output hidden Markov model (IOHMM), logistic regression, and machine learning have been developed by Mubarak *et al*. [22] to predict early dropouts among students based on their interaction logs in an online learning environment. They worked with the data derived from (OULA). This model's accuracy is 84%.

In order to predict academic achievement in relation to internet usage habits, Xu *et al*. [23] have worked with machine learning, neural networks, and support vector machines. They worked with the data on 4,000 pupils' internet usage. The outcome of the presented model demonstrates that behavior control is crucial to academic performance. Social commitment, cognitive commitment, behavioral commitment, and collaboration commitment are the five factors that Redmond *et al*. [24] have studied. emotional commitment for higher education online participation. They used datasets obtained from online models for their work. Experts in online teaching and learning from around the world were informed of the outcome and the process, and their feedback was requested. For the purpose of detecting involvement in online learning, Dewan *et al*. [25] have worked on machine learning, support vector machine (SVM) (Gabor), multiple linear regression (MLR) computer emergency response team (CERT), and Boost (BF). They worked with a dataset of 112 people, of which 80 were men and 32 were women. The proposed model has an accuracy of MLR (CERT) =0.714, Boost (BF) =0.728, and SVM (Gabor) =0.729. Additionally, the classifier attained a correlation of 0.275, 0.329, and 0.306. Deep learning, SVMs, and predictive models (LSTM) for predictive learning analytics in MOOCs' course videos have been developed by Mubarak *et al*. [26]. They worked using a dataset that was downloaded online from (CAROL). This model has a 90% accuracy rate.

According on huge data from the Waheed *et al.* [27]. 's research on deep artificial neural networks, SVM, and logistics regression for student academic performance. They utilized an OULA dataset comprised of 32,593 students over the course of nine months in 2014–2015. This model has an accuracy rate of 88.5%. The CNN model, deep learning model, and SVM model for the online classroom atmosphere assessment system for evaluating teaching quality can Liu *et al*. [28].'s work be considered? They have been working on gathering online sample data. This model produces good results. Work on machine learning, LMS, and data mining for machine learning algorithms using LMS data has been done by Oreki *et al*. [29]. They worked with information obtained from the University of Zagberg. The outcome of the presented model demonstrates that NN modelling can categorize students more accurately than other ML methods.

The academic success of pupils has been predicted using machine learning and electrical discharge machining (EDM) by Okereke [30]. They worked on data samples that were gathered from the 103 first-year students in the University of Nigeria's Computer Science Department. This model's accuracy is 92%. Jiang *et al.* [31] deep's neural network and Betty brain work with feature engineering for identity, which is better sensor-free affect detection, according to Jiang *et al*. [31]. They worked with a dataset of sixth-grade children from a public school in an urban area. The outcome demonstrates that both proposed models' accuracy is equal. Zhang *et al*. [32] studied the learning patterns of university students during the COVID-19 pandemic using edge detection, laparoscopic greater curvature plication (LGCP) feature extraction, AWLGCP and FSR technique, Gabor SVM, and active shape model-SVM. They worked on a dataset that contained 49,920 photos of 47 different people that were each labelled. This model's accuracy rate is 94%.

For the art of staying engaged in problem-solving: automated detection of cognitive engagement, Li *et al*. [33] it's dataset of 61 students, they worked on supervised ML algorithms, cognitive engagement, and facial behaviors. The findings showed that in 82 and 85 segments, respectively, engaged and less engaged states were observed. The relationship between motivation, learning strategies, academic success, and time spent has been studied by Everaert *et al*. [34] using deep learning and surface learning. They have worked with data gathered from 246 student survey responses. According to the results of the suggested model, 19% of students perform poorly on both deep and surface learning techniques.

Deep learning and descriptive statistics have been used by Botelho *et al*. [35] to improve sensor-free affect detection. They worked with data collected from 15 Australian schools totaling 551 pupils being taught by 37 teachers. With the exception of classroom mastery, teacher zeal, and behavioral engagement, the finding demonstrates that the sample distribution is normal. Wu *et al.* [36] have developed mobile-based computer reservation system (CRS) technology for students to learn about entrepreneurship in the classroom. 22 graduate students are enrolled in the 18-week entrepreneurship management course on which they have been working. The findings demonstrate that CRS technology based on mobile devices is a very practical and effective instrument to encourage student involvement.

Waheed *et al*. [37] have worked on machine learning and deep ANN for deep learning models for predicting student academic performance from virtual learning environment (VLE) big data. They have worked on a sample dataset taken from open university learning analysis (OULA). The accuracy of this model is 89. Kumar *et al.* [38] have worked on machine learning, MATLAB, mean square error, and threshold-based segmentation for the analysis of student's performance in virtual learning. They have worked on the dataset taken from http://invertory.data.gov/datase. The result of the proposed model indicates that the performance of the artificial neural network is better than that of the support vector machine. Khajuria *et al*. [39] have worked on survey of various approaches to examine cognitive behavior and academic performance of learner in online learning.

3. SWAYAM PRABHA

Swayam Prabha (SP) is an important step of the MHRD. In this project 32 high-quality educational channels to provide direct to home (DTH) technology, over the entire nation on a round-the-clock basis. The course content of Swayam Prabha is curriculum-based covering different disciplines. This is primarily intended to provide quality educational resources to remote, difficult-to-reach locations where internet access is still an issue. The direct to home channels are employing the GSAT-15 satellite for program telecasts. Some of the important channels of Swayam Prabha are listed in Table 2.

Table 2. Channels and allocations

S. No.	Channels	Director of Channel	Email Id	Name
1	Channel1: humanities, language, literature	Director I/C, EMMRC, EFLU	tnreflu@gmail.com	Prof. T. Nageswara Rao
2	Channel19: IIT PAL Biology	IIT PAL 1 IIT DELHI	AMITTAL@BIOSCHOOL.IITD.AC.IN	Prof. Aditya Mittal
3	Channel 20: IIT PAL: Chemistry	IIT PAL 2, IIT Delhi	ravips@chemistry.iitd.ac.in	Prof. Ravi Singh
4	Channel 22: IIT PAL: Physics	IIT PAL 4, IIT Delhi	jpsingh@physics.iitd.ac.in	Prof. J.P. Singh
5	IGNOU Liberal Arts and Humanities on channel 23	New Delhi's IGNOU	asgupta@ignou.ac.in	Prof. Anju Sehgal Gupta
6	NIOS: Secondary School Education on Channel 27	New Delhi's NIOS	skp@nios.ac.in	Sh. S. K. Prasad, JD (CBC)
7	Channel 30: NPTEL: Mathematics	IIT Madras	ashok@ee.iitm.ac.in	Prof. Ashok Jhunjhunwala

3.1. Digital libraries

The public libraries and institutional libraries in the Indian higher education sector have been playing a vital part in creating readers and enabling enthusiasts to read. The number of students and readers are visiting libraries regularly to access hard copy material of the books, journals, and materials and due to this, libraries in digital form have been increasing in different educational platforms. Although in the present times the number of visits to the library is on a decline due to the digital Indian initiative, the digital library initiative is playing an important role in disseminating information to the students around the clock through digital modes. One of the perfect examples of this digital model is Delhi University Library System (DULS) which makes libraries over 37 in its fold accessible to a wider academic community over the internet. The students, professors, and research scholars can access digital content stored in 63 high-quality electronic databases using the campus network.

4. COURSE

It is a free web-based distance learning program that is built on a huge open online course and is intended for many students who are geographically separated. This ICT-based learning approach could be less regimented or follow the format of a college or university course. Despite the fact that this media does not grant academic credit, the courses it offers may offer a certification, improve job possibilities, or lead to further study. Moocs are typically utilized in higher education settings and job growth procedures. Moocs are essentially a form of online education that a student gets online. These courses use typical classroom resources that have been made available online, as shown in:

- Video lectures that have been filmed or recorded.
- Readings as well as problem sets.
- Online tests and quizzes.
- Interactive learning modules.
- Forums where students can interact with one another.

Asynchronous courses are flexible, self-paced courses as opposed to synchronous courses, which require live attendance and adherence to a set timetable. Figure 1 which shows comparison of synchronous and asynchronous.

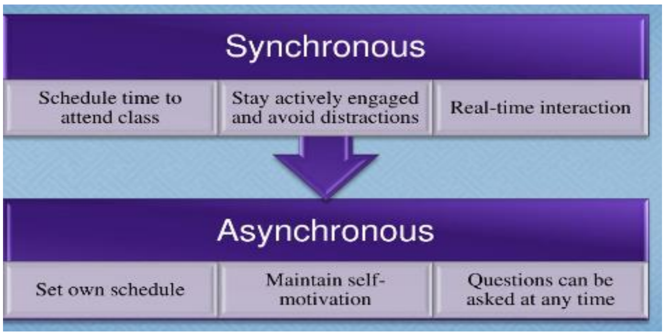

Figure 1. Comparing synchronous and asynchronous learning

4.1. Anti-plagiarism software: URKUND

URKUND is a completely automated digital system that is employed to check plagiarism. It is being successfully used in most of the universities of India and colleges all around the world. It compares each document to one of three primary source areas:

– Published works like books and journals.
– Work that student have already submitted.

URKUND plagiarism detection software has been chosen by the INFLIBNET center (Inter-University Centre of UGC) under the guidance of the Ministry.

5. CONCLUSION

The conclusion of this article deals with the greater application of different ICT modes in higher education institutions. The key among these modes is those which are providing online courses to the students and in a way continuing the teaching learning process even during the corona time. Though ICT is considered as a major medium of enhancing teaching-learning but still due to inadequate technological infrastructure and inexperienced computer students, it is also facing complications and obstacles. It is clear from a survey of the literature that ICT integration is a mediational process that involves ongoing development rather than the production of a finished good. Teachers, students, and school administrators must all put out effort for successful technology integration to occur. This review is critical explains the challenges and solutions for ICT integration in the classroom, as well as the existing circumstances. To enable clearer understanding, the potential gaps in the existing literature are also displayed above directions for future ICT use study. To enable clearer understanding, the potential gaps in the existing literature are also displayed above. ICT in education, especially e-learning as well as distance learning, is best suited to the needs of working professionals with time constraints, allowing them to pursue professional courses at their convenience and thereby adding to the already existing pool of knowledge-driven people leading to better communities. One of the main benefits of adopting ICT tools in education is that it expands access to high-quality education for different groups since it lowers expenses and makes education more accessible.

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