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Developed Model for Analyzing Perception of Learner for Digitize Education during COVID19 using Machine Learning

Md. Iqbal[1]
Research Scholar (Ph.D.)
Deptt. of Computer Science & Engg.
School of Engineering & Technology
Maharishi University of Information Technology

Dr. Manish Varshney[2]
Professor
Deptt. of Computer Science & Engg.
School of Engineering & Technology
Maharishi University of Information Technology

Abstract: The emerging corona virus caused damage on academia all over the globe. This study intends to investigate learner perceptions world using the latest technological culture produced by a COVID-19 pandemic, notably, online learning which has become prevalent internationally and in India specifically. The study employed quantitative research method and a small sample size of Indian learners from the four categories of education in India: universities, technical institutes, colleges of higher education and schools, all of which were selected based on the participant's state of residence. In a pandemic duration, the respondents filled a questionnaire via Google Forms. According to the study, educators are disappointed with digital learning deployed by various advanced learning centers across the globe throughout COVID-19 lockdown, because they don't want digital learning to persist after the outbreak because of poor internet access and a scarcity of materials. However, because of the pandemic, universities should encourage learners more correlative, not just through text it is also through video, augment their e-learning throughout in the pandemic therefore they do not fall behind academically and expend long time on e-learning until traditional learning resumes. Also, India's focus administrators should come back to a conventional learning system as quickly as possible to combat the pandemic, as well as restructure the internet and electricity grid across the country. As a result, this study examines constructs hypothesized in the suggested hybrid model to gain a better understanding of the learners' perspective. A survey of 1439 pupils from an Indian university in the Lucknow area was used to obtain data. K-Nearest Neighbour and Random Forest Algorithms beat other classifier, according to data analysis and study findings. The outcomes of the study will aid in the development of learning applications that take into account students' perspectives on effective network technology.

Keywords: Pandemic, e-learning, Machine Learning, COVID-19, digitize education.

1 Introduction

Admittance to modern information and communication technology (ICT) via network access is building education more accessible, removing the formerly impossible barrier of range and region for those seeking higher education [1]. E-learning necessitates a foundational infrastructure in order for the progression to be successful. In many parts of the emergent globe, digital devices like computers and cell phones are prohibitively expensive. In India, for example, data is not inexpensive, especially given the poverty rate of around 68.8% [2]. The coronavirus sickness was initially discovered in the Chinese metropolis of Wuhan at the end of 2020. By the World Health Organization (WHO), it is the most commonly distributed severe infection, which can cause serious illness and even death [2]. The first COVID-19 case was reported in Kerala on January 30, 2020. COVID-19 was declared a pandemic by the WHO on March 11, 2020, due to its rapid spread [3]. Everything was shut down ever since, including cities, transportation, companies, and educational facilities, impacting having to work everyday life all over the world [4]. The academic community has been alarmed by these disasters, and this anxiety is predicted to spread around the globe. As a result, many governments have shut down those schools, colleges, and other academic facilities in order to restrict the virus's impact [5]. India has also announced that all educational institutions will close on March 18, 2020, affecting education and hence posing a threat to students' future lives [6]. As a consequence, new learning techniques known as mobile learning have emerged as a critical component of education around the world in order to close the academic gap. Many countries employed diverse learning applications like as Google classroom, Google meet, zoom, and others as a result of the worldwide pandemic, according to the 2020 World Bank study. These solutions assist students not just by providing access to materials, but also by allowing those to participate in online classes and interact with teachers in the same way as traditional classrooms did while schools were closed [8-9]. The following is the study's major goals as a guide; we came up with four study questions:

•Proposing a hybrid model based on earlier research hypotheses that consider all relevant factors which determine way participants perceived mobile learning.

•Using machine learning algorithms and survey data to validate the model in order to better understand pupils' perspectives of m-learning adoption during COVID-19.

RQ1: How much e-learning is being done in Indian education throughout the COVID-19 duration?

RQ2: During the COVID-19 era, how much e-learning are pupils in Indian education doing?

RQ3: For the duration of COVID-19 period, how satisfied were pupils with e-learning?

RQ4: What problems do students in Indian higher education institutions face in e-learning throughout COVID-19 duration?

1.1 E-Learning

Remote education is a process that takes place in a wireless classroom using Internet-enabled mobile devices to allow students to study, think, and collaborate from anywhere and at any time. Laptops, tablets, and smart phones or other wireless devices are examples. The term "mobile learning" has been defined in a variety of ways by researchers, including:-

The terminology used to define it are remote learning, a subtype of E-learning, and virtual classrooms using digital devices. Classroom, Mobile-learning, Wireless education, U-learning, Advancement of e-learning, and individualized learning are all terms used to describe mobile learning.

1.2 Wireless Applications/ Appliances

These cellular devices have become increasingly significant all around world as a result of current developments and techniques. The sorts of portable devices used in e-learning could be described as follows in modern environment: -

Laptops:

Laptops and notepads are examples of portable electronics that are commonly used in everyday life by all people in society. These machines use a number of wireless techniques to let users receive information, namely USB cables, Bluetooth, wireless connections, and some other infrared gadgets.

Desktop:

It's a laptop-sized device that's larger than a cell phone but less than a notebook. It can be used for many things, such as watching presentations, sharing images, and video conferencing.

Smart Phone:

It is telecommunication gadget that performs extra functions than a desktop computer. It provides us with a high-resolution screen, a camera, a flexible Smartphone, and a variety of streaming systems and tools.

Other Movable devices:

Devices such as the Xbox, media players, joysticks, online media transmitters, gaming systems, and streaming video fall under this category.

2 Literature Review

In wireless classes, mobile learning entails the use of wireless devices like cell phones, notebooks, and desktop computers, as well as wireless network. Because mobile learning is so significant, it's crucial to figure out what technology can meet learners' needs and expectations. As a result, mobile learning acceptance in universities and colleges and successful mobile software implementation, digital learning usage, and critical components of m-learning approval must all be examined. Several previous studies used statistical approaches to study and find the most important drivers for student uptake of mobile education [10]. Several studies used conventional theories and models including such TAM, TPB, and pupil’s Perception of M - learning Utilizing Interned Allowed Portable Devices throughout COVID-19 TRA, UTAUT, and others [11]. The underlying paradigm is Davis's Technology Acceptance Model [12], which he devised and described. TAM's model is missing system characteristics, which could have a huge effect on m-learning acceptance. However, this model can be used to determine a student's attitude toward mobile learning. Another survey proposed a model, like the upgraded De-Lone and McLean's model, which indicated the standards of quality elements for increasing the use of m - learning [13], however this model does not include TAM components. As a consequence, one of the most important aspects of an m-learning system's effectiveness is measuring students' acceptance, which can include a variety of factors such as students' needs, features of the system, and content quality. As a result, this [14] study combines the TAM, UTAUT, and updated models to create a hybrid model that incorporates all of the important features. The TAM factors of observed mobility and satisfaction, which drive users' behavior toward e - learning, were only defined in the theoretical model of acceptance and the use of technology model. In his literature review [16][17], Lee discovered that resources including equipment / software distribution, and also technical support, can impact students' preparedness to accept and use mobile learning efficiently. Furthermore, past research projects evaluated theoretical models using statistical techniques. Purposive sampling approaches are applied, which include just those individuals who are relevant to the research domain and are interested in it. As a result of the findings in the literature, this study will examine all elements during the pandemic time in order to better understand student perception of M-learning for the duration of COVID-19.

3 Proposed Framework

This study's methodological approach outlines the full hypothesis outlined in the subcategories Specified needs, User perceptions, and Acceptance Testing. These three subsections contain critical factors such as standard data, standard content, standard device, offering service, user-friendly, expectancy value, application level of satisfaction, sense of mobility, user motive, uses of digitization, and real-world m-learning usage. The hypothesis proposed among numerous constructs in the study model is described in Figure 1.

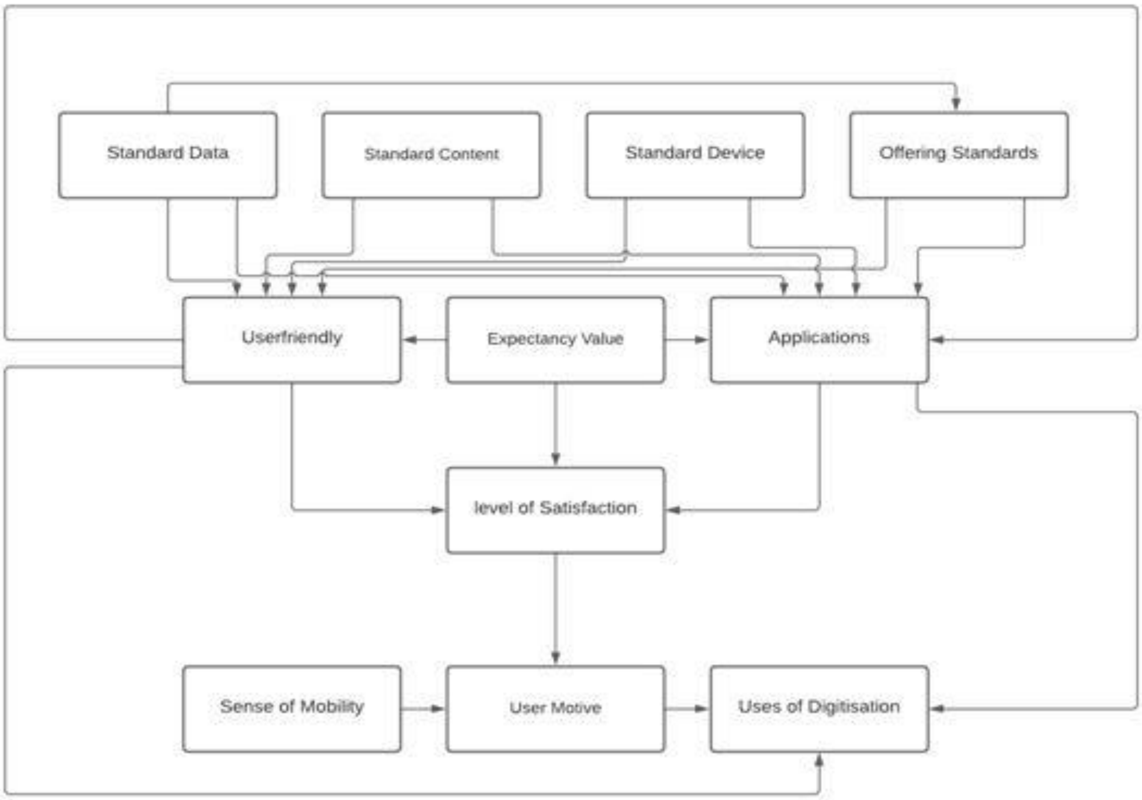

Figure 1 Proposed Framework System

3.1 Framework Components

3.1.1 Standard Data

It refers to the effectiveness and reliability of mobile educational content such course contents, exercises, photographs, and quizzes [18]. It delivers well-defined, speed, flexible, and appropriate data to users. As a consequence, the progress of m - learning is down to the quality of available information. Learners are only motivated to adapt and adopt digital resources if the information is of greater quality, according to Cheng [19]. Several prior researches have shown that the quality of information impacts pupils' adoption of mobile studying at institutions. The user satisfaction of use is influenced by the quality of the data.

3.1.2 Standard Contents

It's a part of the calculation for information disclosure. Updates both to course material and the evaluation questions are referred to as standardized content. In the context of M-learning, [20] emphasizes the importance of improving the quality of content provided by all platforms. The user satisfaction of use is influenced by the quality of the content.

3.1.3 Standard Devices

It refers to system functionality, dependability, accessibility, ease of use, recognition, and a user-friendly interface design. According to previous study [18], the platform's quality is determined by the user's viewpoints; therefore good system quality has a favorable impact on mobile learning's simplicity of utilize and utility. The user satisfaction of use of a system is affected by its quality.

3.1.4 Offering Standard

It refers to the ability to access mobile services from any location and at any time. Usability, accessibility, engagement, content utility and material adequacy all need to be prioritized [11]. The user satisfaction of usage is positively influenced by service quality.

3.2 Consumer Trust on Framework

3.2.1 User-friendly

This concept is defined by Davis [11] as the degree to which a person believes that using technology is self-sufficient or requires no effort. This notion is referred to as "relief from great trial" or "autonomy from complexities”. Many researches have found that a user's willingness to use m-learning technologies is related to their effort potential [22]. The perceived simplicity of use has a beneficial impact on satisfaction.

3.2.2 Expectancy value

Expectancy value theory is divided into three categories: intrinsic value, attainment values, and utility values. In the context of mobile learning, this concept is used to understand pupils' educational motivations and academic achievement. According to studies, the EVT is used to predict learners' intentions to complete a task quickly and their performance [25]. Expectancy value effects perceived ease of usage in a positive way. The focused point is intrinsic value, attainment value and utility value inside this section.

3.2.3 Applications

The TAM model was the first to utilize this concept, and it demonstrated how much a individual believes that utilize a meticulous technology will help them accomplish better work [11][22]. The COVID-19 pandemic encouraged universities to transition to online education. Appearance of utility positively influences m-learning satisfaction

3.2.4 Level of Satisfaction:

When a learner engages with a digital platform directly, satisfaction has been defined as the happiness or confidence that the learner experiences [20]. As a consequence, the authors think that happiness seems to have a favorable impact on the actual use of mobile learning. The willingness to use m-learning in the future is positively influenced by satisfaction.

3.3 Consumer Adoption of Framework

3.3.1 Sense of Mobility

The process of learning that takes happen practically everywhere and at any time is known as mobility or ubiquity. To put it another way, it allows students to learn in a challenging world [25]. This new component, mobility, was incorporated the UTAUT model to identify whether or not a student is familiar with mobile applications and whether or not they wish to utilize them [21]. The behavioral intention to use e-learning is positively influenced by the impression of mobility.

3.3.2 User Motive

It refers to a learner's intention to benefit from e - learning and to apply it all in the upcoming [24]. It has been identified as a parameter to assess that influences a learner's decision to adopt active technology [22]. The intention to use m-learning has a beneficial impact on its actual utilization.

3.3.3 User of Digitization

Whether or not mobile learning technology is used determines the true use of m-learning. It is the TAM model's final construct, and it has no bearing on the previous constructs [26]. Previous research has suggested that this function Object component is crucial, and that it may be used to explore how learners actually use mobile learning by looking at a variety of characteristics. As a result, there is no theory for this concept.

4 *Proposed Framework Implementation*

4.1 A review of online learning was performed during COVID-19

COVID-19, according to Li [26], has had a global influence on education, forcing nearly 1.2 billion pupils out of the classroom and necessitating the exploration of alternative methods of educating schoolchildren. They stated that language apps, digital guidance, videoconferencing, and digital class’s software have ruptured since the eruption of COVID-19, with investments in education estimated to grow from USD 18.66 billion in 2019 to USD 350 billion by 2025, prompting many systems to provide free classroom services. BYJU, Bangalore Edtech Company that specializes in online tutoring was founded in 2011 and has since risen to become the world's wealthiest EdTech firm. However, other researchers [15][13] believe that e-learning falls short of classroom learning due to a lack of access to digital resources

Such as computers, web access, as well as the digital literacy. Similarly, in the COVID-19 era, it was determined that less than half of American students are attending online classrooms due to chronic absence and non-performance of homework. In 2018, it was discovered that only 21.3 percent of the people had access to technology in their schools [21], whereas Lau argues that a proper university setting is needed for deep knowledge.

4.2 Designed Theoretical Framework

This framework reflects how the recent innovation wide-spreads and jump up in vogue in the range of specific demographic area. In order to place it in a different fashion, individuals in a specific social system adapts with the recent activity or idea, which is further transmitted to other people in a similar social system or also to the larger groups from where the idea comes. In the 19th century, Skinner and Watson focused on how people learn from this theory.

4.2.1 Data Collection for Theoretical Framework

During COVID 19, learners who are presently using mobile technology in teaching and learning for study were given online questionnaires to better understand their perspectives of various factors affecting digital learning acceptance. An online questionnaire is the only option to collect data in this study, specifically throughout COVID-19. Students from a single Meerut college are among the participants. As a result, an online Google form was used to record the responses of 1439 students. Because the questions are identified as mandatory, any partial or invalid responses are successfully prevented in this study. Furthermore, the study attempted to obtain primary genuine data from all college students.

4.2.2 Theoretical Framework Channels

This study takes a quantitative approach. The questionnaire's items were derived from earlier research, with some lingering questions included in case of the COVID-19 situation. A 5 Likert scale with few values was employed as the measurement scale to assess the constructs in the proposed framework, ranging from Strongly Disagree to Strongly Agree.

5 *Result Discussions*

5.1 Data Analysis

We employed machine learning methods to examine the data and evaluate the proposed theoretical framework for this study. Machine learning is a technique for predicting future events with high accuracy utilizing both historical and new data. Machine learning algorithms work by training a model and then testing it on current data to provide efficient results. It forecasts dependency or predicted links between the independent and dependent variables affecting student opinions on digital learning acceptability in the scope of this research.

5.2 Theoretical Framework Validation

Machine learning classifiers are utilized in this study to investigate the relationships between the constructs in the suggested hybrid theoretical model. As a result, Logistic Regression, Support Vector Machine, Nave Bayes, Decision Tree, Random Forest, and K-Nearest Neighbor classifiers are utilized. They all are representing Table 1.

Table 1. Representing prediction among algorithms and user-friendly

S. No.	Different Algorithms	Performed Algorithms Accuracy
1	Logistic Regression	89.05
2	Support Vector Machine	89.44
3	K-Nearest Neighbor	96.02
4	Decision Tree	84.41
5	Nave Bayes	91.57
6	Random Forest	96.87

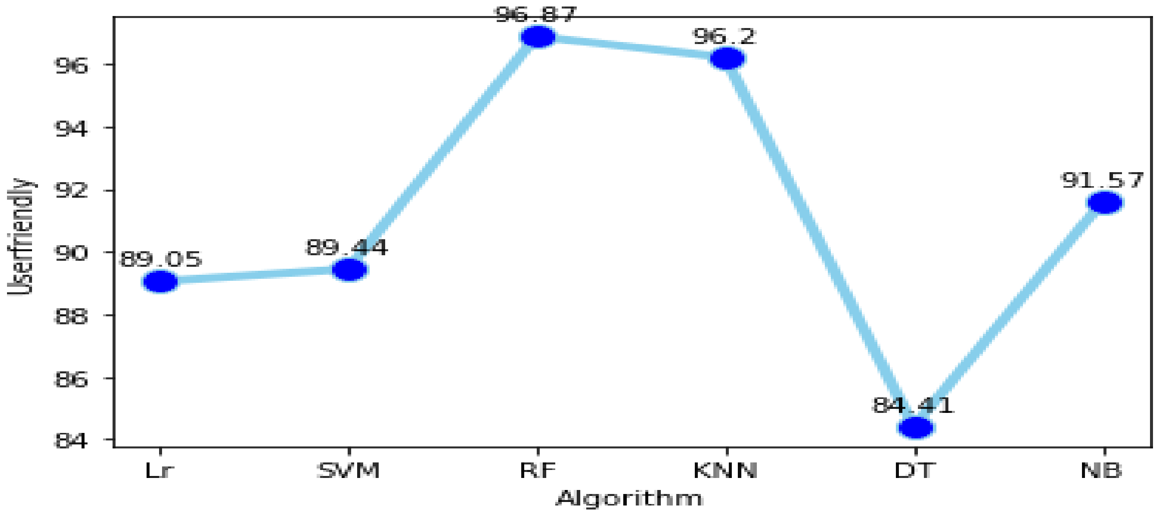

Figure 2 Accuracy analysis prediction among algorithms and user-friendly

Table 2. Representing prediction among algorithms and application

S. No.	Different Algorithms	Performed Algorithms Accuracy
1	Logistic Regression	87.32
2	Support Vector Machine	88.01
3	K-Nearest Neighbor	94.27
4	Decision Tree	85.61
5	Nave Bayes	89.02
6	Random Forest	94.43

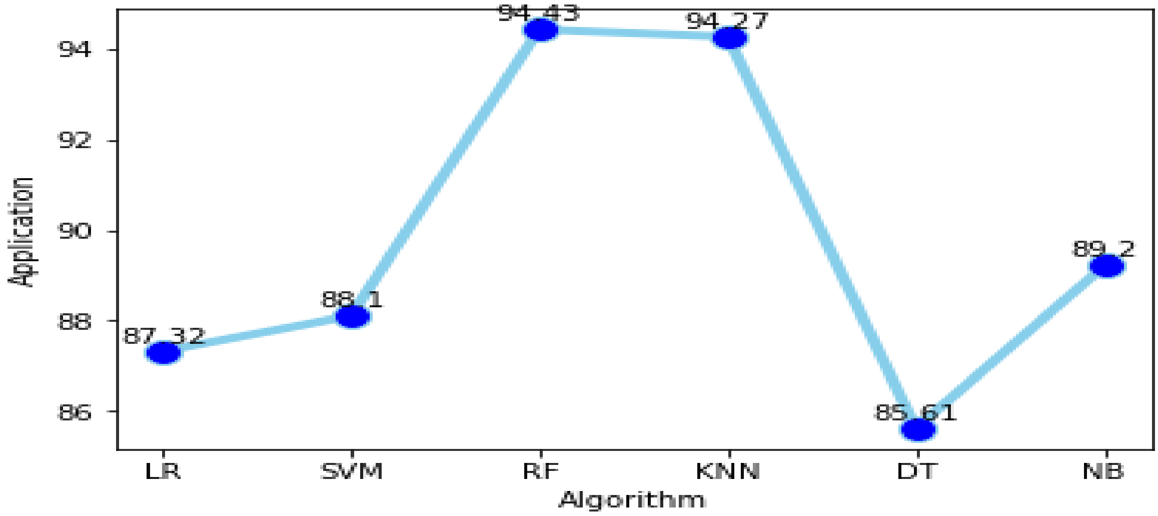

Figure 3 Accuracy analysis prediction among algorithms and application

Table 3. Representing prediction among algorithms and offering standards

S. No.	Different Algorithms	Performed Algorithms Accuracy
1	Logistic Regression	80.07
2	Support Vector Machine	78.01
3	K-Nearest Neighbor	78.77
4	Decision Tree	76.05
5	Nave Bayes	80.04
6	Random Forest	81.59

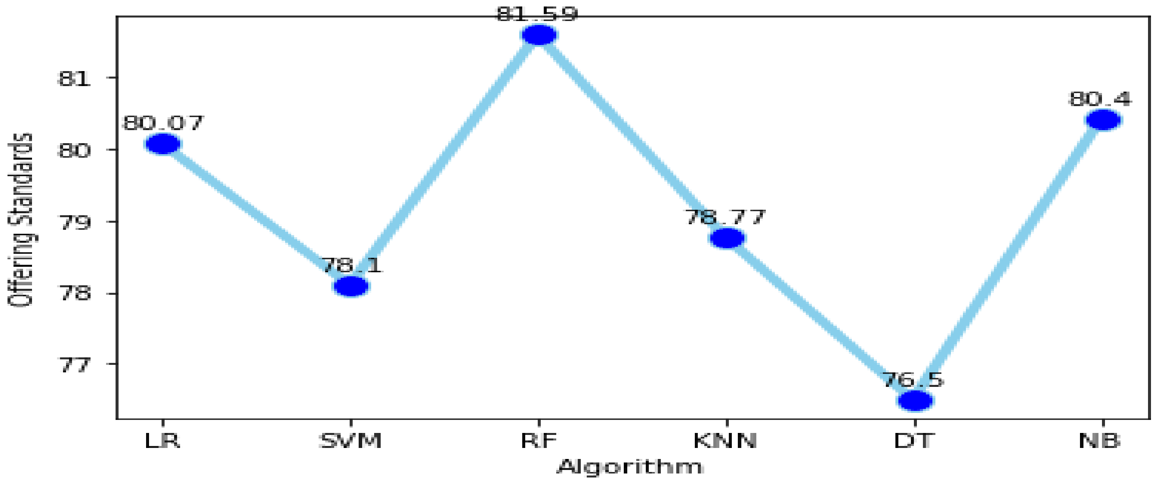

Figure 4 Accuracy analysis predictions among algorithms and offering standards

Table 4. Representing prediction among algorithms and Level of Satisfaction

S. No.	Different Algorithms	Performed Algorithms Accuracy
1	Logistic Regression	78.64
2	Support Vector Machine	80.79
3	K-Nearest Neighbor	90.02
4	Decision Tree	82.76
5	Nave Bayes	80.29
6	Random Forest	91.87

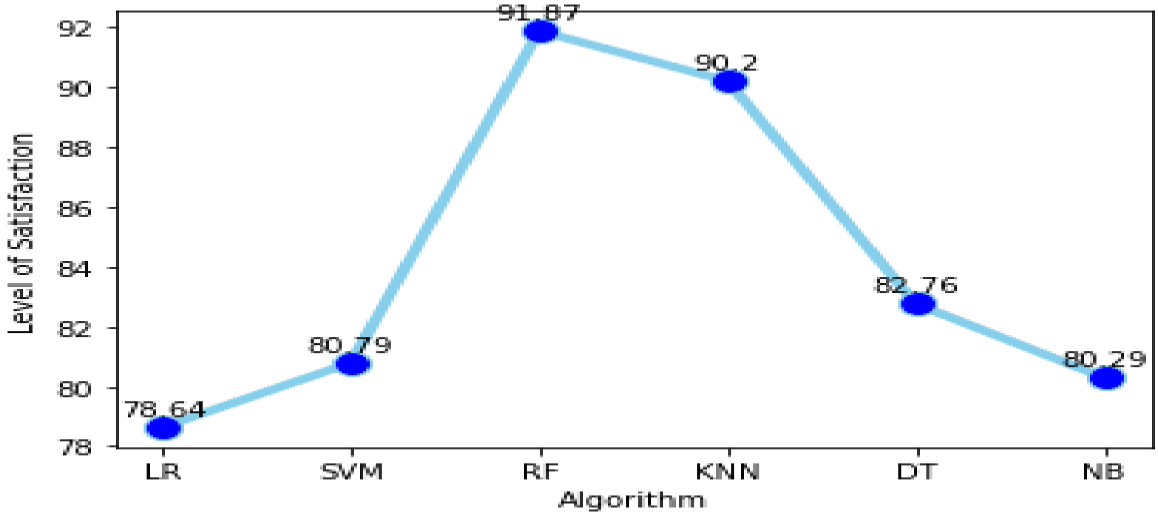

Figure 5 Accuracy analysis predictions among algorithms and Level of Satisfaction

Table 5. Representing prediction among algorithms and user motive

S. No.	Different Algorithms	Performed Algorithms Accuracy
1	Logistic Regression	90.76
2	Support Vector Machine	90.68
3	K-Nearest Neighbor	91.88
4	Decision Tree	89.63
5	Nave Bayes	89.29
6	Random Forest	91.01

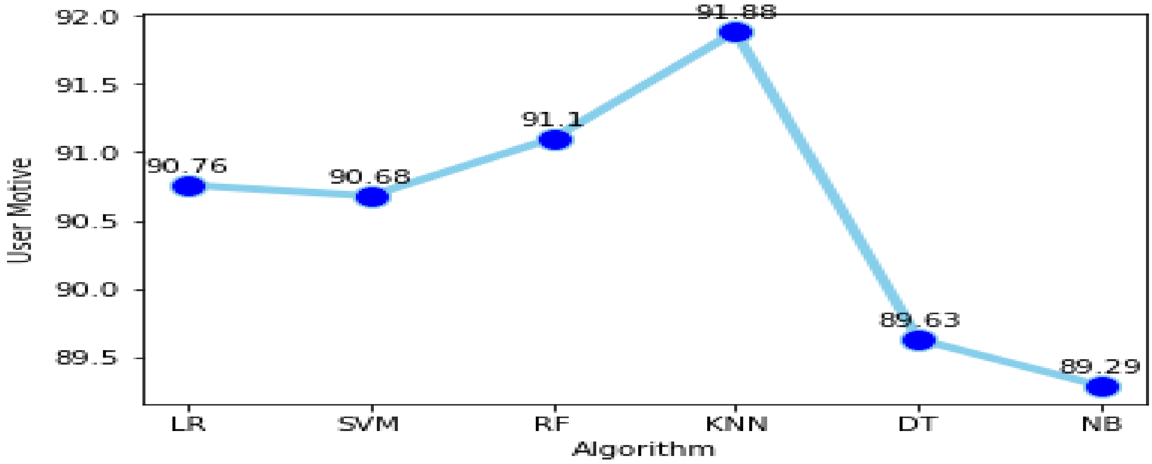

Figure 6 Accuracy analysis predictions among algorithms and user motive

Table 6. Representing prediction among algorithms and uses of digitization

S. No.	Different Algorithms	Performed Algorithms Accuracy
1	Logistic Regression	93.47
2	Support Vector Machine	93.75
3	K-Nearest Neighbor	91.03
4	Decision Tree	93.52
5	Nave Bayes	87.29
6	Random Forest	94.07

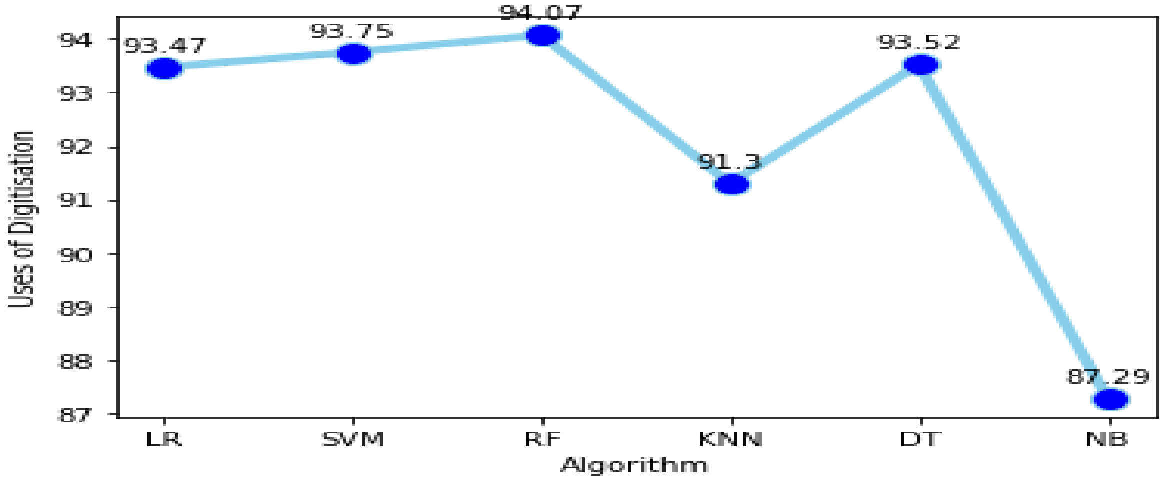

Figure 7 Accuracy analysis predictions among algorithms and uses of digitization

5.3 Sampling and Questioners

Examining the four study topics immediately structures the data presentation and analysis. The data acquired from the poll revealed that women made up 64.6 percent of the respondents, while men made up 30.1 percent. Furthermore, 61.4 percent of the respondents were university students, 33.5 percent were students at technical institutes, 5.3 percent were college students, and 4.2 percent were school pupils. Table 1 shows the different levels of pupils who took part. Table 2 shows the extent to which Indian education system used digital system throughout the COVID-19 period. During the COVID-19 pandemic, free learning platforms like Google Classroom, WhatsApp, and Zoom were particularly popular, according to the poll, with the majority of the alternatives being WhatsApp, Google Classroom and Zoom.

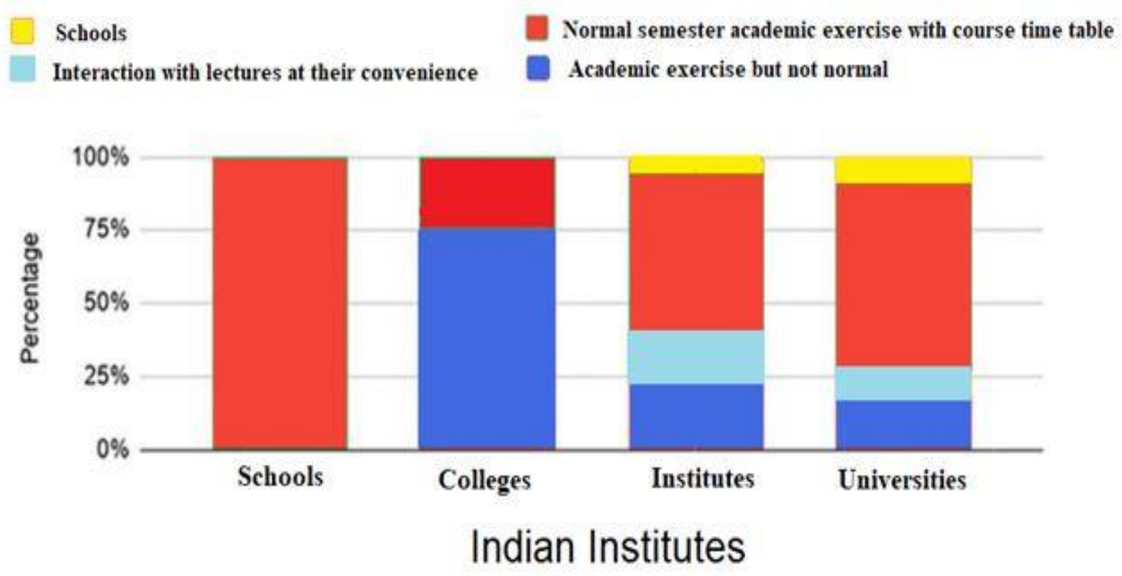

Figure 8 Shows the level of academic learning in Indian schools during the COVID-19 pandemic.

Table 1.Representing the academic levels of learners who took part in the survey from Indian educational system.

Category of Education	**Participation of People**	**Percentage of Participation**
Schools	146	10.14
Colleges	280	19.45
Technical Institutes	697	48.43
Universities	316	21.95
Calculating Values	1439	100

Table 2.Shows the different types of class mode given by Indian students during the COVID-19 epidemic.

Classroom Mode	**Participation of People**	**Percentage of Participation**
WhatsApp Platform	141	9.79
Zoom Platform	227	15.77
Skype Platform	128	8.89
Webex Platform	163	11.32
Google Meet	301	20.91
Google Classroom	412	28.63
Google Duo	67	4.65
Calculating Values	1439	100

Table 3. During the COVID-19, Indian students used a lecture approach.

Delivery Mode	**Participation of People**	**Percentage of Participation**
Text Format	278	19.31
Audio Format	327	22.72
Video Format	314	21.82
Multimedia Format	233	16.19
Camera Based	165	11.46
Combined All	122	08.47
Calculating Values	1439	100

Table 3 shows that many internet classes were mostly text-based, which might be linked to text using less bandwidth compared audio and video offerings. This is significant because one out of every 10 respondents did not engage in any online courses during the COVID-19 pandemic.

Table 4.Students in the Indian education system faced several problems during the COVID-19 pandemic

Online classes Issues	**Participation of People**	**Percentage of Participation**
Internet	378	26.26
Power Supply	227	15.77
No Enough Data	279	19.38
Boring Classes	183	12.36
Background Noise	198	13.75
Laziness	174	12.09
Calculating Values	1439	100

The problems, as shown in Table 4, can be split into four categories. Cluster one, which included poor infrastructure and services, accounted for 26.26 %, cluster two, which glanced at individual factors, accounted for 15.77 percent, cluster three, which resolved with financial power, specifically the incapability to purchase enough data, accounted for 15.77 percent, and cluster four, that also looked at natural conditions, accounted for 15%. These data indicated that infrastructure concerns were the most significant hindrance to efficient online learning by Indian school pupils throughout the COVID-19 period, following by person and environment. Financial factors were the least troublesome for online learning's success.

6 *Conclusions*

The findings are comparable to those of prior studies with a large number of factors. As a result of the current pandemic, education has transitioned from a physical classroom to online mobile learning. As a result, this investigation was experimentally used to find features from students' perception that influence individuals' attitudes towards mobile learning for studying during COVID-19 using machine learning techniques. Only a few researches have used machine learning to forecast the components. We are able to generalize for digital learning consumption among pupils focus on student opinions during COVID-19 using machine learning as a consequence of the data and research. The findings also reveal important factors to consider when creating mobile learning systems, with the aim of growing pupil use of e - learning for academic purposes. It will also educators better understand how students perceive these features in terms of improving mobile learning teaching approaches.

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