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Student's Perception towards Mobile learning using Interned Enabled Mobile devices during COVID-19

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Abstract

INTRODUCTION: The novel corona disease disrupted education all around the world. This shifted people to mobile learning in real time wireless classroom from the physical face-to-face classroom.

OBJECTIVE: Mobile learning has been present for years but the use of mobile learning is more in the current scenario due to COVID-19. However, people's acceptance of mobile learning education at institutions is still low. Thus, this research seeks to understand the student's perspective by analysing constructs hypothesized in the proposed hybrid model.

METHOD: Data is collected using a survey from an Indian institute of the Meerut region with a total of 1022 students.

RESULT: Data analysis and research findings showed that Random Forest and K-Nearest Neighbour Algorithms outperforms than other classifiers in predicting the dependent variables with better accuracy rate, precision, and recall value in this study.

CONCLUSION: The research findings will help the designers and software development to design learning applications considering the perspective of students with respect to 5G technology.

Keywords: Mobile learning, COVID-19, 5G technology, Adoption, Machine learning algorithm.

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1. Introduction

The education system is always preferred and based on a traditional face-to-face classroom where learning is done in the school every day. But the situation changed when the world suffers from an infectious disease called COVID-19 caused by a coronavirus [1]. At the end of 2020, this novel coronavirus disease was first identified in the Chinese city of Wuhan. According to the world health organization (WHO), it is the fastest transmission respiratory disease that can also develop severe ailment and can lead to person death too [2]. India also witnessed the first COVID-19 case in Kerala on 30 Jan 2020. Seeing this rapid spread of COVID-19 WHO declared it as a pandemic on March 11, 2020 [3]. Since, that time, everything including cities, transportation, business, and educational institutions has been shut down which affected people's daily lives all over the world [4]. This tragedy has aroused concern in the education industry, and this anxiety is likely to spread around the world. Hence, many countries close their schools, colleges, and other Education institutions to lessen the impact of the virus [5]. India had also shut all institutions of education from March 18, 2020, which affects education and hence became a concern of student's future life [6]. So, to bridge the education gap an innovative learning methodology known as 'Mobile learning' became a very important part of education worldwide. According to the 2020 World Bank report due to the global pandemic, many countries used different learning applications such as Google classroom, Google meet, zoom, and many more. These systems help students not only give access to material but also engage them in online classes and interaction with teachers like traditional teaching as schools were closed [8-9]. Despite various advantages of digital learning, there are complications with technology adoption. Thus, to use mobile learning even after the health shortage dies down it is necessary to first understand the student's perspective and perception towards mobile learning. The following is the study's major goal:

- To recognize the important determinants and their relationship based on existing literature towards m-learning adoption.
- Proposing a hybrid model based on previous research theories that include all essential factors to find out how students feel about m-learning.
- Validating the model through machine learning algorithms with the data collected from the survey to understand student's perception throughout COVID-19 towards m-learning adoption.

1.1 Mobile learning

Mobile learning is learning that uses Internet-enabled mobile devices in a wireless classroom to allow students to learn, communicate, collaborate, and access learning from any location and at any time. Laptops, tablets, and mobile phones or wireless devices for distance learning are examples of mobile devices [7]. Mobile learning now outperforms other types of learning because to these improvements. The term mobile learning has been defined in different ways by different researchers as follows: -
It is distance learning, a subset of E-learning, and online education using digital devices are the terms used to describe it. Ubiquitous learning, M-learning, hand-held learning, U-learning, Extension of e-learning, learning while mobile, portable learning, and personalized learning are all terms used to describe mobile learning. Mobile phones, tablets, podcasts, desktops, e-readers, and laptops are all examples of mobile learning resources that are used in the classroom. The latest technologies and techniques are used to access information using mobile device features such as mobility and screen size all over the world. To summarize, mobile learning can be defined as learning that uses mobile technology to enable anyone to access digital information, resources, platforms, websites, and other resources regardless of predetermined location or changing time.

1.2 Mobile devices

An electronic device or gadget that may be utilized from anywhere is referred to as a mobile device. A handheld computer is another name for it. These devices are designed to be portable and fit in the palm of your hand. Some mobile devices, such as smart phones, cell phones, tablets, E-readers, Personal digital assistants (PDAs), and smart watches, can be used to do activities in the same manner as desktop or personal computer. These portable devices are crucial in the globe, thanks to the latest technology and trends. The sorts of mobile devices used in mobile learning can be classified as follows in current life: -

Laptop: There are several portable devices, such as laptops and Notepad that are widely utilized in daily life by all members of society. These laptops assist users in getting information using a variety of wireless technologies, including USB cable, Bluetooth, wireless network, and other infrared devices.

Tablet PC: It's a personal computer that's bigger than a smartphone but smaller than a notebook computer. It's a touch screen gadget with a 7 or 10.1-inch display and an easy-to-use user interface (UI). It's used for a variety of things, including watching presentations, reading E-books, sharing images, video conferencing, and more.

PDA (Personal Digital Assistant): It is also called as palmtop device or computer. This device can be connected Due to portability we can connect this device remotely with the help of internet.

Smart Phone: It is a device used for communication that has additional functions as compared to PDA. It provides us an advanced screen display, camera, foldable smart phone, and different streaming platforms and applications [4].

Servers: It's a computer that sends data or educational materials to other computers or students. A server, host computer, or master refers to the data sent by the computer. Many services are made possible by some servers. Databases, e-mail, files, Short Message Service (SMS), Files, Proxy, servers, and many others are among them.

Mobile phones: Mobile phones have evolved into a vital means of communication. The latest 5G technology has boosted the use of smartphones with a variety of extra capabilities such as music, video, camera, high-resolution displays, and moving pictures.

E-readers: It is commonly known as e-book readers. They have the same design and structure as tablet, but it is designed for e-books reading, online content, and downloaded books. Some examples of e-readers are Amazon kindle, kobo, and noble book.

Other mobile devices: These are devices like x-box, media players, joy-pad, digital media receivers, game consoles, and video players.

1.3 Mobile learning compatibility with 5G Features compatibility

It is learning that is done remotely on digital learning platforms. It is also a learning which uses wireless and mobile technology by extending desktop learning to handheld wireless devices for education. Thus, the advanced version of this cellular network 5G technology could enable students to learn both synchronously and asynchronously. 5G technology helps in boosting mobile learning in terms of high bandwidth, more capacity, more mobility, reliability and availability of network for learning in wireless classroom [32-34]. The 5G technology and its devices will also allow the students to learn with the better content visualization and attending class reducing signal lost and attenuation. Here are some of the major features of 5G technology that boost mobile learning for education with its architecture as follows:

- Mobile learning enables and support learners to learn from anywhere and anytime whereas 5g technology architecture provides fast service deployment of internet with high speed using cellular network for efficient mobile learning.

- High capacity/low latency is used to support performance related data and handle differentiation sensed data bounded tightly to

- Quality of Service differentiation capabilities 5G target: 1000 times higher mobile data volume per area. Thus, the 5G technology provides data rates beyond 1Gbps while for latency three different levels considered with range from 1-10m. Furthermore, multiple traffic types are supported between them periodic and event driven.

- Mobile learning needs privacy and high security. This data security is achieved with rapidly changing architecture of 5G and its features for the learning process.

- Mobile learning requires long battery hence, 5G offers lifetime10 time longer battery life based on sleep time and patterns that can be enforced on a service specific manner.

- Mobile learning gives Network reliability and availability but using 5G technology it ranges from 95% to 99% from low to high.

- 5G technology provides high bandwidth, more capacity, mobility and network availability for mobile learning.

This research paper is structured in a way as Section 2 sums the past studies and factors that are considered in developing the research model. It also summarizes the proposed model constructs and their hypothesized relationship. Section 3 describes the research methodology process including data collection technique and instrumentation used to validate the model Sections 4 describes the data analysis results following student’s perception towards mobile learning. Lastly, Section 5 describes the paper's conclusion with limitations and the scope of future study.

2. Related Work

Mobile learning in wireless classrooms is a learning that consist wireless devices such as mobile phones or 5G devices, laptops Personal Digital Assistant (PDA) and wireless access points. As the use of mobile learning is essential it is important to determine the technology that can satisfy learners need and requirements. Thus, Mobile learning use in institutions for higher education and successful mobile applications implementation, mobile learning usage, essential factors of m-learning acceptance need to be considered for its adoption. Using statistical methodologies, several existing researches investigated and discovered the most significant drivers for the adoption of mobile education among students [10]. Traditional theories associated with models such as TAM, TPB, TRA, UTAUT including others, were used in several investigations [11]. Among these, the base model is the Technology Acceptance Model (TAM) which was developed and explained by Davis [12]. This model focuses on two essential constructs of subjective beliefs: perceived ease of use and perceived usefulness that are significant constructs for estimating and predicting learner's adoption of Information systems or information technology [12]. TAM lacks system characteristics in the model which can play a key role in influencing acceptance of m-learning. But this model act as a useful model for determining student's perspective towards mobile learning. Another, research study proposed model such as updated De-Lone and McLean's model (DL&ML) who explained the importance of quality factors for enhancing the usage of mobile learning applications [13] but this lacks TAM factors. The unified theory of acceptance and use of technology model (UTAUT) also specified only the constructs of TAM including perceived mobility and enjoyment which influences users' behavior towards mobile learning. In the research study conducted by Lee [16], he discovered that resources including hardware and software availability, as well as technical support, can influence students' willingness to accept and apply mobile learning effectively [17]. As a result, one of the most important components of a mobile learning system's performance is determining students' acceptance, which can include a variety of factors such as students' needs, system features, and the quality of the content. Hence, this [14] study integrates TAM, UTAUT model with updated (DL&ML) to develop a hybrid model covering all the essential factors. Several previous research studies also determine the effectiveness of mobile learning in wireless classroom with significant growth of mobile learning using 5G technology wireless devices. Among the most important feature that 5G incorporates in mobile learning according to studies is the high data rate, reliability and network availability through variety of content types from video files, animations to interactive possibly collaborative learning games. Furthermore, previous research studies employed statistical technique to evaluate theoretical models. Purposive sampling techniques is used which includes only the participants that are relevant and are interested in the research domain. The instruments and tools used were Cronbach alpha for questionnaire and SPSS, SEM, PLS-SEM, AMOS are used for analyzing the factors relationships. Regression algorithms are used to determine the relationships between constructs. This research study does not follow the statistical approach for findings and analysis of data. Various machine learning algorithms are used to predict the relationships between the factors and the convenience sampling approach is employed in this study. So, the conclusions from the literature cause this research to analyze all the factors during the pandemic period to understand the student perception towards mobile learning during COVID-19.

3. Proposed Hybrid Research Model and Hypothesis development

The following research framework proposed in this study explains the entire hypothesis mentioned in the following subsections namely System specifications, User beliefs, and User Acceptance. The influential factors in these three subsections are information quality, content quality, system quality, service quality, perceived ease of use, expectancy-value theory, perceived usefulness, satisfaction, perceived mobility, behavioural intention, and actual use of m-learning. Below Figure 1.describes the hypothesis proposed among various constructs in the research model.

3.1 System Specifications

3.1.1 Information quality It means the effectiveness and quality of mobile education content such as lecture materials, assignments, pictures, and quizzes [18]. It gives well-defined, updated, flexible, and appropriate information to users. Therefore, information quality plays an essential role in the growth of mobile learning. Cheng [19] also indicated that students get motivated to adopt and accept online learning only if it provides better quality content. Several previous studies showed that information quality influences the students positively to accept mobile learning in institutions. Another study revealed that student perception also influenced the information quality of mobile learning applications [14-15]. Thus, student's choice of mobile learning content will make it easy to utilize mobile learning and increase their education performance. So, the following assumption is made following some past studies:

H1(a): Information quality positively influences perceived ease of use.

H1(b): Information quality positively influences perceived usefulness.

H1(c): Information quality positively influences service quality.

3.1.2 Content quality: It is a subpart of information quality. Content quality means the enhancement in course content itself and the assessment questions also. Concerning the mobile learning context [20], highlights the value of enhancing the quality of the material given by all platforms. Better quality content gives a student an insight to learn easily, understand relevant information, freedom, and competence in mobile learning [18]. Both scholars claimed that the content that necessitates being studied will be perceived as valuable and easy if such enhancements are made with mobile learning platforms [11]. Thus, it is necessary to understand the importance of content quality so that instructional designers fully utilized the student's feedback and maximize the system performance according to user needs. Based on the above definitions, its impact can be described as:

H2(a): Content quality positively influences perceived ease of use

H2(b): Content quality positively influences perceived usefulness.

3.1.3 System quality: It means system functionality, reliability, accessibility, easiness, acknowledgment, user-friendliness interface design. Previous research [18] indicated that the quality of the platform depends on the user’s views hence good system quality positively influences mobile learning ease of use and usefulness. Another study [11] claimed that it is an essential factor that significantly impacts mobile learning platforms used by students. Therefore, it is extremely important to collect users' experiences from time to time towards mobile learning systems. Hence, the following hypothesis can be made based on previous research as: -

H3(a): System quality positively influences perceived ease of use.

H3(b): System quality positively influences perceived usefulness.

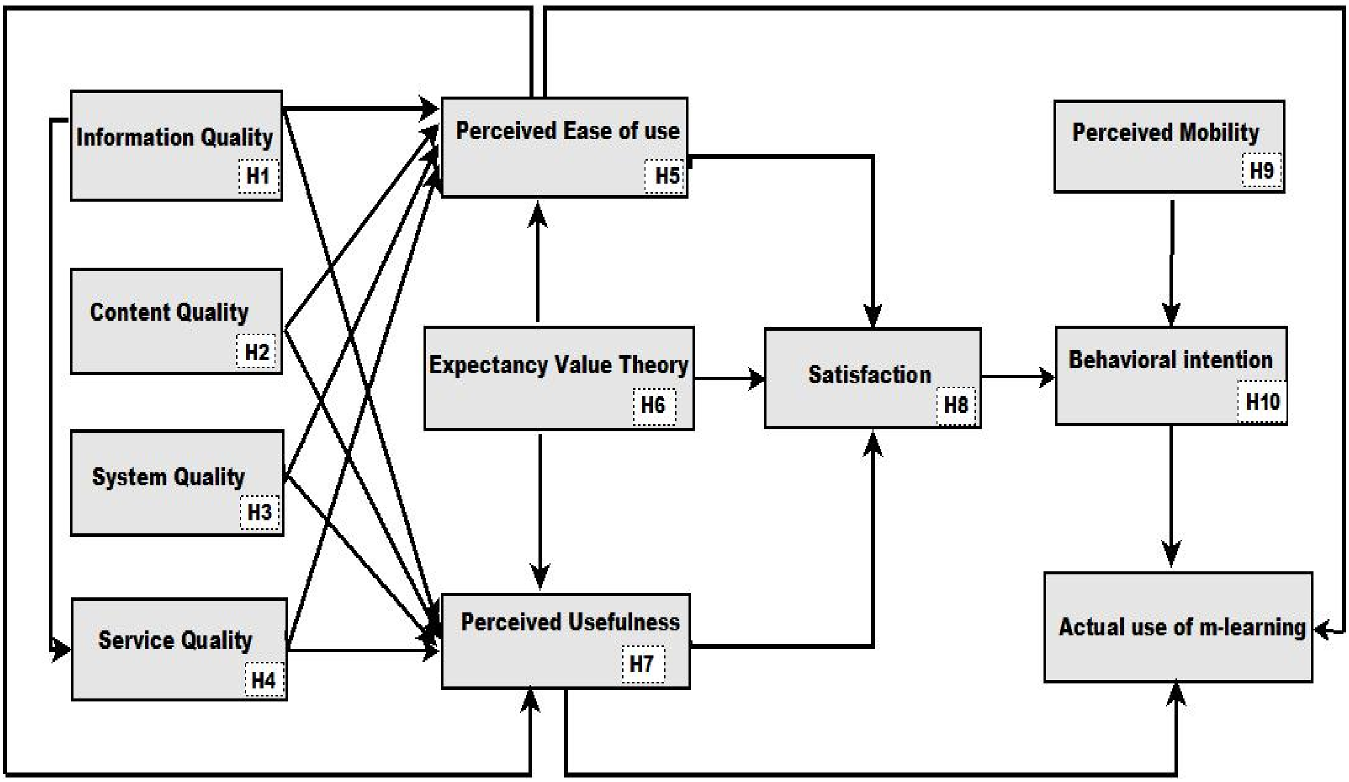

Figure 1. Proposed research model

3.1.4 Service quality: It means the availability of mobile services from anywhere and anytime. It must focus on usability, accessibility, interaction, the usefulness of the content, and the adequacy of the information [11]. Previous study Daft and Lengel [30] showed that accuracy, authenticity, and kind of information interchanged over a mechanism were crucial to the performance effectiveness of m-learning tools [21]. In another study, Almaiah and Al Mulhem [20] explained that service depends on the user specifications and requirements availability of content, trust, ease to use, and the response of the mobile learning system.

Thus, this construct is important in mobile learning to be studied [18]. All these theories let us hypothesis this as: -

H4(a): Service quality positively influences perceived ease of use.

H4(b): Service quality positively influences perceived usefulness.

3.2 User beliefs

3.2.1 Perceived ease of use: This concept was introduced by Davis [11] as the degree to which the individual believes that using technology is self-sufficient or requires no effort. This is derived from the notion of "freedom from tremendous trial" or "freedom from complexity." Many researchers have found that users' intention to use m-learning technology is positively correlated with their effort likely [22]. Furthermore, this study reveals that the more students believe m-learning is simple to utilize for learning tasks, the more they use it [13]. According to this study, students will adopt m-learning if it is simple to use and they are satisfied with it. As a result, it shows a positive correlation with actual m-learning usage. As a result, the hypothesis might be phrased as follows: -

H5(a): Perceived ease of use positively influences satisfaction.

H5(b): Perceived ease of use positively influences the actual use of m-learning

H5(c): Perceived ease of use positively influences perceived usefulness.

3.2.2 Perceived usefulness: Davis [11] TAM model was the first to use this terminology and explained the extent to which an individual believes that employing a certain system will help an individual perform better at work [22]. This is later termed as performance expectancy by different researchers. Previous research has found that using this methodology to test learners' acceptance of mobile learning, indicates that they will employ it if it enhances their performance [23]. The advantage of the learning applications prompts the learners to use and adapt for gaining knowledge. Perceived usefulness or performance expectancy [24] It was determined to be a major predictor of m-learning adoption since it had a strong impact on student's intention to adopt m-learning, as per the study. In the case of online education, the COVID-19 pandemic prompted universities to move to it.

As a result, the hypothesis formulated as: -

H6(a): Perceived usefulness positively influences satisfaction towards m-learning.

H6(b): Perceived usefulness positively influences the actual use of m-learning.

3.2.3 Expectancy value theory: Expectancy value theory has been broadly classified into three factors namely intrinsic value, attainment values, and utility value. This terminology is employed to understand student's educational motives and academic performance in the meaning of mobile learning. Researches revealed that the EVT is used for predicting the intention of learners to finish a task in an easy way and performance [25]. According to this study, its three categories are significant that affect learner's acceptance of m-learning and assist in predicting learner's satisfaction [26]. Also, the students' performance was influenced positively because of the advantage in the learning applications [22]. If the learners believe that mobile learning is beneficial then eventually their purpose to use distance learning will be essential. Therefore, the following hypothesis is made: -

H7(a): Expectancy value positively influences perceived ease of use.

H7(b): Expectancy value positively influences perceived usefulness.

H7(c): Expectancy value positively influences satisfaction.

1) Intrinsic value

It means the learners feel motivated to use mobile learning regardless of reward. Users believe that learning through mobile is enjoyable [25]. It is generally used to determine how students perceive the education method. Since there is a pressure determinant associated with the learning process, it is a requirement to deliver a more engaging, enjoyable, and challenging education [26].

2) Attainment value

Attainment value is linked to a learner’s performance that depends on individual values and ways. Several studies emphasized a strong correlation between intention and attainment value in many fields, in addition to web-based programs. According to [14], tasks will have a higher achievement value if they allow the learner to validate key aspects of his or her self-schema. From the perspective of technology-enhanced education, [24] found a favourable association between achievement value and intention to continue. As a result, the learner's decision to employ m-Learning may be influenced by attainment value. Therefore, it is included in the research study.

3) Utility value

It is an extrinsic motivation that will change the learner’s response where it is considered that m-learning does not give an immediate reward [21]. Nevertheless, the reward will resemble in the long run. Therefore, it is described as the degree to which learners understand the learning activity correlates to their prevailing and future goals [26]. To boost student acceptance and usage of m-learning, it is critical to make educational activities more agreeable.

3.2.4 Satisfaction: Satisfaction is the enjoyment or confidence that learner feels towards mobile learning platforms when interacts with them directly [29]. Previous research has revealed that distance learning has a beneficial impact on learner satisfaction, which will boost m-learning adoption. According to this study, satisfaction is an important factor for both intend to use and actual use. The actual use of mobile learning systems is influenced by satisfaction [21]. As a result, this study assumes that contentment has a beneficial impact on actual mobile learning usage. As a result, the hypothesis is asserted as: -

H8: Satisfaction positively influences behavioural intention to use m-learning.

3.3 User Acceptance

3.3.1 Perceived mobility: Mobility or ubiquity is the learning process that takes place virtually anywhere and anytime. In other words, it enables the learners to study in a dynamic environment [25]. This additional construct mobility was added to the UTAUT model to evaluate if a student has awareness of this construct, then adoption of learning applications and their intention to use will be high [21]. Therefore, it is one of the essential constructs shaping the learners' purpose to use m-learning systems effectively [23]. Thus, in this study hypothesis was formulated between perceived mobility and behavioural intention to determine the intention to use mobile learning by students.

H9: Perceived mobility positively influences behavioural intention to use m-learning.

3.3.2 Behavioural intention: It means the learner's intention that finds mobile learning beneficial and intends to use it in the future [24]. It is recognized as a parameter to measure that affects the learner's decision whether to use (Actual use) mobile learning [22]. Various studies measured that if the user finds mobile learning simple to utilize, it affects the actual use of mobile learning platforms. All these facts let us hypothesizing this relationship:

H10: Behavioural intention positively influences the actual use of m-learning.

3.3.3 Actual use of m-learning: The Actual Use (AU) of m-learning refers to the using or not using mobile learning technology. It is the last construct of the TAM model which does not influence other constructs [26]. Previous studies claimed that this constructor factor is significant which helps to investigate the actual use of mobile learning by the learners using different factors. Hence, the hypothesis is not formulated for this construct. Below Table1 describes as follows:

Table 1. Instrument construct and their sources.

Construct	Measures	Sources
Information Quality	1. Mobile learning provides relevant information and updated content. 2. Information provided by m-learning is easy to understand. 3. M-learning provides organized content and information.	[7],[10],[31]
Content Quality	4. It is more engaging as learning through using graphs, videos, audios are possible. 5. Do you feel revising course becomes easier with mobile learning.	[10]
System Quality	6. It helps me to ask queries to the teachers without any fear. 7. It is easy to upload and download files using mobile learning. 8. Mobile learning application is compatible with different platforms.	[7],[10]

Service Quality	9. Mobile learning applications provide services anytime and anywhere. 10. Do you think m-learning is a more efficient approach to receive feedback? 11. Mobile learning acts as a good learning resource.	[11],[21]
Perceived Ease of Use	12. I find M-learning easy to use. 13. It is easy for me to find required information using mobile learning. 14. I find mobile learning platforms user friendly.	[18],[27],[29]
Perceived Usefulness	15. Mobile learning improves my skills and solve study related problems. 16. It helps me to watch recorded content in future. 17. M-learning enables me to take tests and submit assignments quickly.	[27],[29]
Expectancy value theory	18. Mobile learning helps me to learn in many ways and provides several learning fields. 19. It helps me to record my performance and control my learning progress. 20. I feel assured using m-learning tools. 21. I feel assured using m-learning content.	[18],[27],[28]
Satisfaction	22. You find mobile learning enjoyable and interesting. 23. Mobile learning satisfies my educational needs. 24. I am satisfied with the mobile learning.	[18],[29]
Behavioural intention to use	25. I plan to use m-learning to get updated my subject understanding with the latest alterations. 26. I plan to use mobile learning usually for my study purpose. 27. I would recommend others to use mobile learning in future. 28. I prefer to use mobile learning in future.	[18],[27]
Perceived mobility	29. It helps to save transportation cost and time due to mobility. 30. Learning by mobile helps me learn anytime and anywhere.	[21],[28]
Actual use of m-learning	31. I am using m-learning on daily basis. 32. I choose to use m-learning.	[29]

3.4 Methodology

Data collection and participants

To understand the student's perception considering various factors towards mobile learning adoption during COVID 19, online questionnaires are distributed among students who are currently using mobile learning technology for study. The employ of an online questionnaire in this study, specifically during COVID-19 is the only method to collect the data. Participants are students from one college in the Meerut region. Hence, a total of 1022 student's survey response is recorded through an online Google form. The questions are marked as compulsory, thus incomplete or invalid answers are avoided in this research successfully. Moreover, the research aimed to collect primary real data of all the students of college.

Instrumentation

This research employs a quantitative technique. The questionnaire items are prepared from the previous literature with some additional questions in case of the COVID-19 situation. A five-point Likert-type, ranging from Strongly Disagree to Strongly Agree, was employed as the measurement scale with values 5-1 was adopted to test the constructs in the proposed framework. Hence, the survey includes 32 items for eleven constructs namely Information quality (3), Content quality (2), System quality (3), Service quality (2), Perceived ease of use (3), Perceived usefulness (3), Expectancy value theory (4), Satisfaction (3), Perceived mobility (4), Behavioural intention (2), Actual use of M-learning (2) to verify the hypothesized relationships of the proposed framework.

4. Research and Findings

4.1 Data Analysis

We have used machine learning algorithms to analyse the data and validate the proposed theoretical model of this research. Machine learning is a technique that helps to predict future events based on both current and historical data effectively. Machine learning algorithms provide a solution to complex problems and build the predictive model by training the classifier and testing on the new dataset to produce efficient results. In the context of this study, it predicts the dependency or hypothesized relationships between the independent variables and dependent variables concerning student's perspectives for mobile learning acceptance. Thus, supervised learning classification algorithms are employed in this study using python.

4.2 Results of theoretical research model validated using Machine learning classifiers

In this study, machine learning classifiers are used to study the correlations among the constructs in the proposed hybrid theoretical model. Thus, various classification algorithms such as Logistic Regression, Support Vector Machine (SVM), Naïve Bayes, Decision Tree, Random Forest, and K-Nearest Neighbour classifiers (KNN) are employed. The analysis using these algorithms is carried out using Sci-kit module of python in Jupiter-notebook by applying the k-fold cross-validation technique on collected data. Based on Table 2. and Figure 2**.** the findings showed that both Random Forest and KNN had the best results in predicting the perceived ease of use by the constructs information quality, content quality, system quality, service quality, expectancy value theory in an accuracy rate of (Random Forest = 96.57% and KNN = 96.08%) as compared to other classification algorithms.

TPR: True Positive Rate, ***FPR:*** False Positive Rate, ***SVM:*** Support Vector Machine, ***KNN:*** K-Nearest Neighbour

Table 2. Predicting the perceived ease of use by information quality, content quality, system quality, service quality, expectancy value theory

CLASSIFIER	ACCURACY (%)	TPR	FPR	PRECISION	RECALL	F-MEASURE
LOGISTIC	88.45	0.924	0.280	0.833	0.927	0.877
SVM	88.74	0.837	0.175	0.881	0.838	0.859
RANDOMFOREST	**96.57**	**0.987**	**0.137**	**0.917**	**0.991**	**0.946**
KNN	**96.08**	**0.986**	**0.162**	**0.904**	**0.991**	**0.945**
DECISION TREE	81.01	0.917	0.512	0.751	0.919	0.912
NAÏVE BAYES	92.46	0.915	0.150	0.904	0.919	0.912

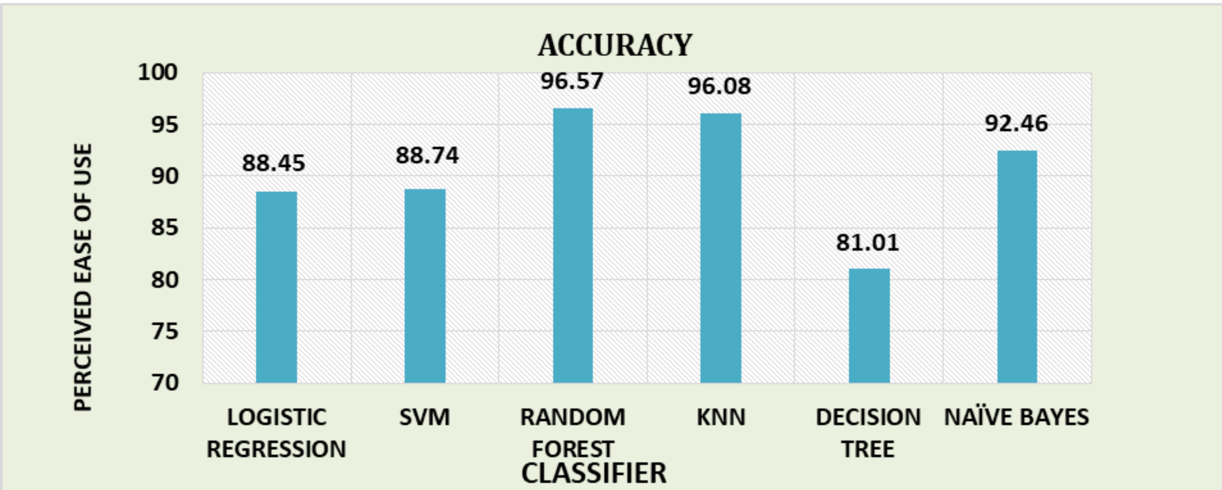

Figure 2. Accuracy analysis in predicting perceived ease of use

Hence these results supported hypothesized relationships H1(a), H1(b), H2(a), H3(a), and H4(a), and H7(a).

Table 3. Predicting the perceived usefulness by information quality, content quality, system quality, service quality, expectancy value theory, perceived ease of use

CLASSIFIER	ACCURACY (%)	TPR	FPR	PRECISION	RECALL	F-MEASURE
LOGISTIC	87.08	0.891	0.270	0.821	0.890	0.854
SVM	87.27	0.883	0.223	0.846	0.882	0.864
RANDOMFOREST	**93.73**	**0.981**	**0.201**	**0.873**	**0.983**	**0.924**
KNN	**93.63**	**0.974**	**0.164**	**0.892**	**0.974**	**0.931**
DECISION TREE	85.61	0.873	0.352	0.795	0.870	0.868
NAÏVE BAYES	89.43	0.870	0.129	0.904	0.873	0.888

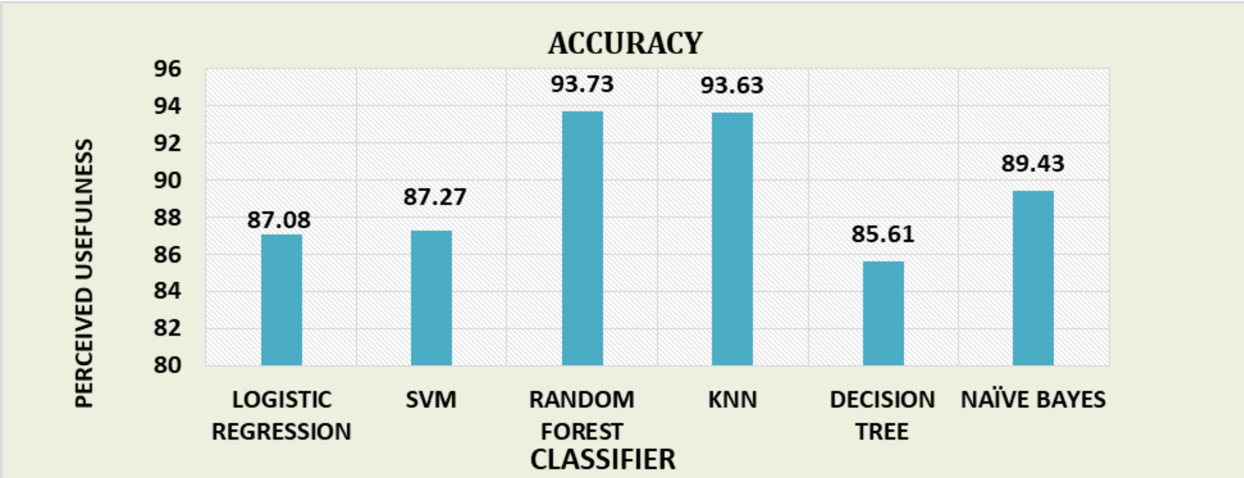

Figure 3. Accuracy analysis in predicting perceived usefulness

According to the results in Table 3 and Figure 3. better performance was given by the random forest algorithm in predicting perceived usefulness as compared to other classifiers. Random forest algorithm and KNN was able to use information quality, content quality, system quality, service quality, expectancy value theory, perceived ease of use in predicting perceived usefulness with an accuracy of 93.73% and 93.63% accordingly, these H1(c), H2(b), H3(b), H4(b), H7(b), and H5(c) were supported.

Table 4. Predicting the service quality by information quality

CLASSIFIER	ACCURACY (%)	TPR	FPR	PRECISION	RECALL	F-MEASURE
LOGISTIC	**80.21**	**0.965**	**0.320**	**0.904**	**0.967**	**0.944**
SVM	78.77	0.961	0.360	0.903	0.963	0.934
RANDOMFOREST	**80.24**	**0.984**	**0.320**	**0.906**	**0.987**	**0.945**
KNN	78.08	0.823	0.240	0.913	0.824	0.866
DECISION TREE	76.20	0.905	0.340	0.894	0.907	0.884
NAÏVE BAYES	79.65	0.965	0.300	0.903	0.967	0.934

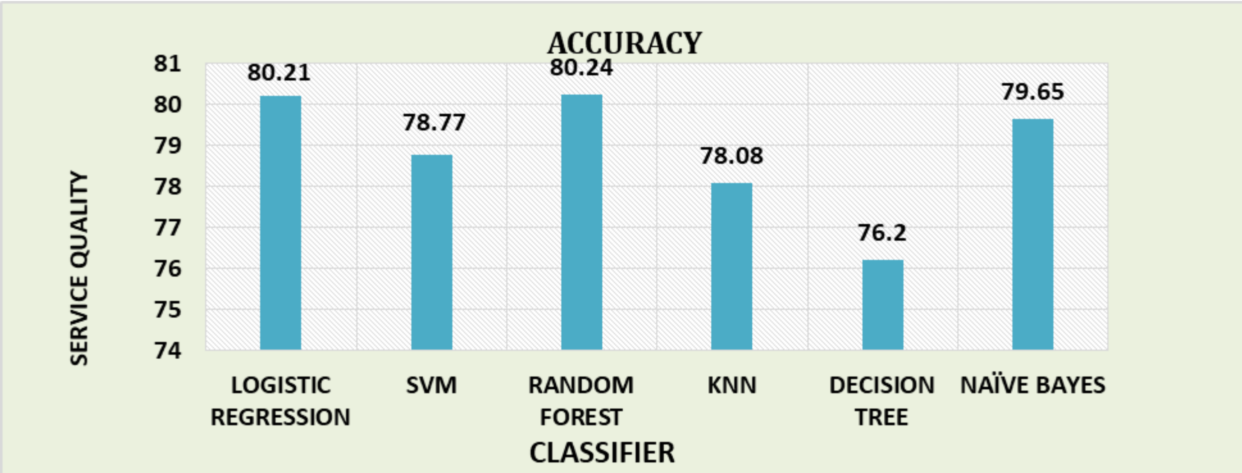

Figure 4. Accuracy analysis in predicting service quality

The results in Table 4. and Figure 4. suggest that logistic regression and Random Forest perform better than other classifiers when it came to predict the service quality using information quality. Both classifiers logistic regression with accuracy 80.21% and random forest with 80.24% predicted efficiently. They have high performance with respect to other values including TPR, precision, and recall value. In case of Logistic Regression TPR value 0.965, precision (0.904), and recall value (0.967) while in Random Forest classifier it has also higher TPR (0.904), precision, and recall value among all classifiers. Hence H1(c) hypothesis is supported.

Table 5. Predicting the Satisfaction by perceived ease of use, perceived usefulness, expectancy value theory

CLASSIFIER	ACCURACY (%)	TPR	FPR	PRECISION	RECALL	F-MEASURE
LOGISTIC	78.46	0.721	0.262	0.714	0.607	0.701
SVM	80.33	0.740	0.246	0.738	0.682	0.711
RANDOMFOREST	**91.77**	**0.802**	**0.385**	**0.801**	**0.732**	**0.765**
KNN	90.31	0.785	0.311	0.821	0.730	0.723
DECISION TREE	82.67	0.704	0.285	0.781	0.721	0.720
NAÏVE BAYES	80.23	0.701	0.286	0.769	0.504	0.606

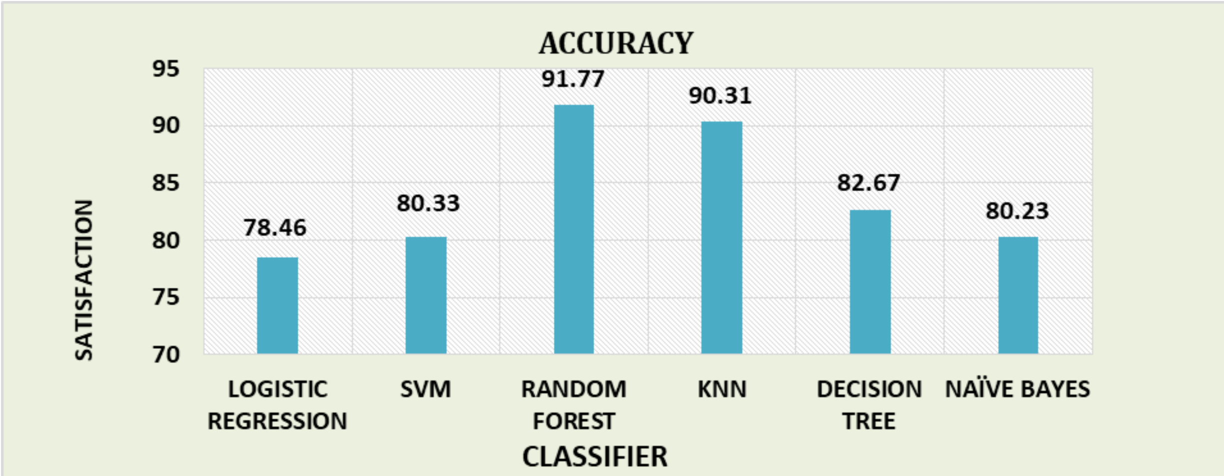

Figure 5. Accuracy analysis in predicting Satisfaction

According to the results from Table 5. and Figure 5. the constructs such as perceived ease of use, perceived usefulness, expectancy value theory predict satisfaction towards mobile learning with accuracy of 91.77% by the Random Forest classifier better than all others. In addition to it has higher TPR (0.802), precision (0.801) and recall value (0.732). Hence H5(a), H6(a), H7(c) hypothesis were supported.

Table 6. Predicting the behavioural intention to use by satisfaction and perceived mobility

CLASSIFIER	ACCURACY (%)	TPR	FPR	PRECISION	RECALL	F-MEASURE
LOGISTIC	90.40	0.954	0.327	0.872	0.958	0.912
SVM	90.40	0.957	0.311	0.878	0.958	0.916
RANDOMFOREST	90.70	0.914	0.295	0.883	0.951	0.915
KNN	**91.48**	**0.963**	**0.278**	**0.890**	**0.965**	**0.925**
DECISION TREE	89.40	0.896	0.295	0.874	0.926	0.850
NAÏVE BAYES	89.33	0.929	0.262	0.892	0.930	0.910

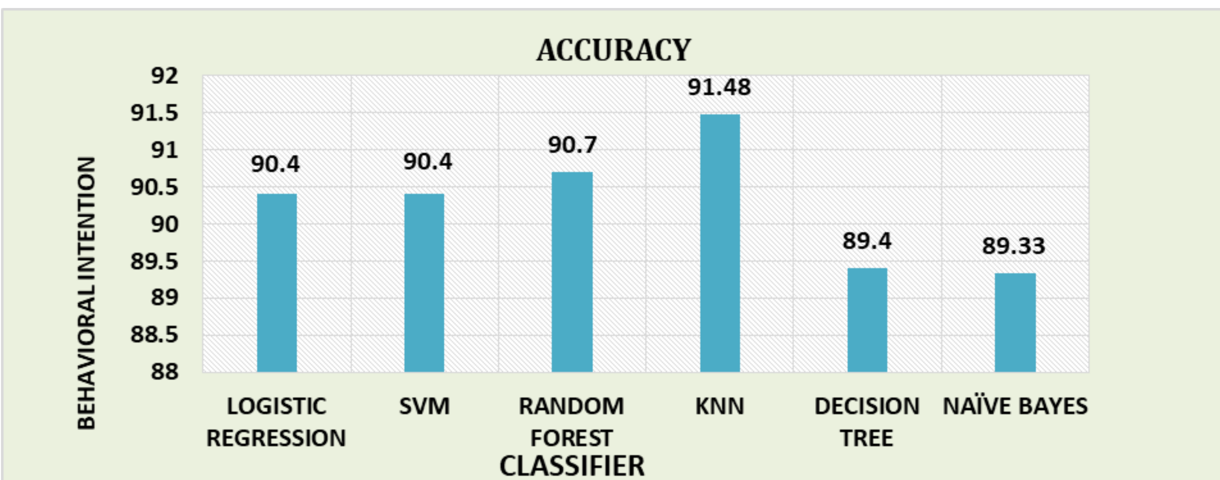

Figure 6. Accuracy analysis in predicting behavioural intention

From Table 6. it is clear that KNN is the best classifier to predict Behavioural intention towards mobile learning using satisfaction and perceived mobility with an accuracy of 91.48%. Hence H8 and H9 hypothesis were supported.

Table 7. Predicting the actual use of m-learning by behavioural intention to use, perceived ease of use, perceived usefulness

CLASSIFIER	ACCURACY	TPR	FPR	PRECISION	RECALL	F-MEASURE
LOGISTIC	93.34	0.989	0.266	0.943	0.993	0.967
SVM	93.54	0.964	0.214	0.948	0.967	0.967
RANDOMFOREST	**93.83**	**0.990**	**0.266**	**0.943**	**0.993**	**0.970**
KNN	91.29	0.989	0.263	0.937	0.993	0.964
DECISION TREE	**93.64**	**0.899**	**0.254**	**0.943**	**0.993**	**0.967**
NAÏVE BAYES	86.08	0.912	0.350	0.876	0.901	0.888

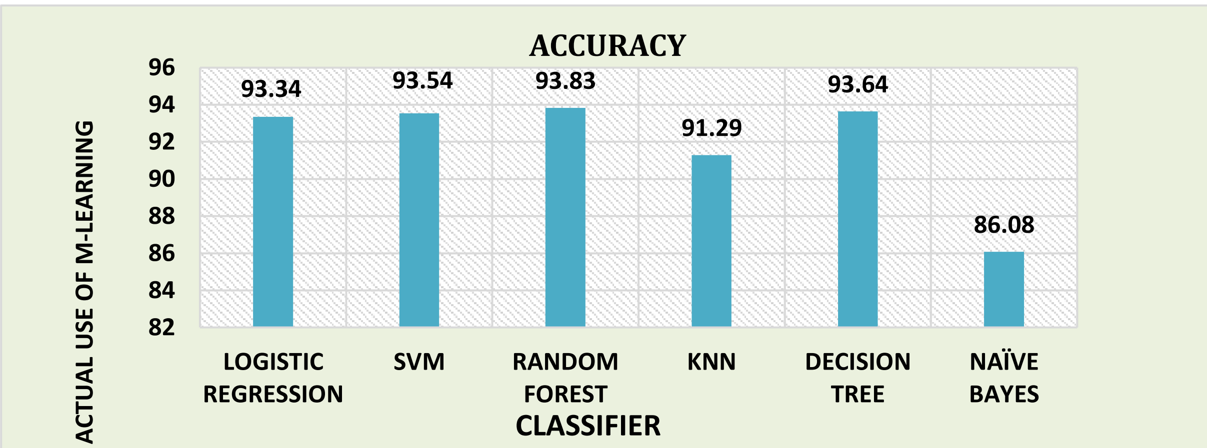

Figure 7. Accuracy analysis in predicting Actual intention to use m-learning

The results in Table 7. and Figure 7. show that Random Forest with accuracy of 93.83% and decision tree with 93.64. These classifiers perform better in predicting Actual use of m-learning using behavioural intention, perceived ease of use and perceived usefulness better than other classifiers. Hence H10 hypothesis is also supported.

5. Conclusion and Recommendations

The study results are similar to the previous studies with many variables. But this study proposed a hybrid research model using TAM, UTAUT and De-Lone and McLean's model with essential factors to understand the student's perspective towards mobile learning during COVID-19. The current pandemic scenario shifted the education from process from physical classroom to online mobile learning. Therefore, this study was empirically applied to find the factors from student's perceptions that influence students towards mobile learning for studying during COVID-19 using machine learning algorithms. The research model is validated using six classifiers such as Logistic Regression classifier, Decision-tree classifier, Naïve Bayes classifier, Random Forest classifier, SVM classifier, and KNN classifier using Sci-kit learn in python. The results showed that constructs such as perceived ease of use, perceived usefulness are the predicted variables with the highest accuracy among all other constructs with an accuracy above 93%. Thus, these are the important determinants of mobile learning adoption that influence students to use mobile learning. Another, constructs such as Service quality, Satisfaction are predicted with an approximate accuracy of 80% using different classifiers. Lastly the behavioural intention and actual intention to use mobile learning are the key factors that predict student's perception to use mobile learning with an accuracy around 90% using Random Forest and KNN algorithms. It is observed after the analysis that Random Forest and KNN are majorly two best algorithms that give higher performance results in terms of accuracy, precision and recall value in comparison to other classifiers for prediction of mobile learning constructs of the proposed model. There are only few studies to predict the factors using machine learning. Hence the result findings and analysis help us to generalize the results for mobile learning adoption among students from student's perception during COVID-19 using machine learning algorithms. The findings also give the understanding of the key factors to develop mobile learning platforms such that it could increase the use of mobile learning among students for study purposes. Also, it will help the teachers to understand the perception of students with these factors to improve the teaching practice using mobile learning.

Recommendations for future study

The study findings are based on one institute of the Meerut region. Thus, it opens a scope of research in other institutes to understand better the perception of students. Secondly, its main aim is to understand only the student's perspective towards mobile learning technology. Also, in further studies the use of 5G technology for mobile learning must be focused as it limits the disadvantages of 4G technology and meets learner requirements. Another, It is suggested that the teachers' perception towards the actual use of m-learning should be covered in the succeeding studies to gather further information about the influencing constructs and a holistic aspect of the implementation of these learning systems.

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