E-learning System Adoption: A Select Study in Indian Context

Thesis

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by

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DECLARATION

I hereby *declare* that the research synopsis entitled "**E-LEARNING SYSTEM ADOPTION: A SELECT STUDY IN INDIAN CONTEXT**" which is being submitted to the **National Institute of Technology Karnataka, Surathkal** in partial fulfilment of the requirements for the award of the Degree of **Doctor of Philosophy in Management** is a *bonafide report of the research work carried out by me*. The material contained in this thesis has not been submitted to any University or Institution for the award of any degree.

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CERTIFICATE

This is to *certify* that the research synopsis entitled **"E-LEARNING SYSTEM ADOPTION: A SELECT STUDY IN INDIAN CONTEXT"** submitted by **Ms. Vanitha P S**, (Register Number: 1650446SM16F10) as the record of the research work carried out by her, is *accepted as the Research Thesis submission* in partial fulfilment of the requirements for the award of degree of Doctor of Philosophy.

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DEDICATION

This thesis is dedicated to my beloved parents, teachers and friends.

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EXECUTIVE SUMMARY

This study aims to analyse e-learning adoption in the Indian context. This study is suggesting recommendations for the improvement of e-learning adoption in higher education institutions. Different dimensions of the e-learning framework are focused on along with the e-learning challenges. Both qualitative and quantitative analyses were carried out in this study. In addition, the Information System Theories and Learning Theories are used in this study to refine the e-learning system parameter and learners' attributes. As part of this research, the e-learning barriers were identified and categorised into two main divisions: technological and individual barriers. These barriers were analysed through quantitative analysis. To validate the research model, responses were collected from 704 participants through a questionnaire survey conducted in India. The PLS-SEM (Partial Least Squares-Structural Equation Model) describes the relationship between constructs in the research model. Apart from this, the correlation between gender and e-learning adoption are analysed through quantitative analysis. Total 425 responses were considered to perform the analysis. The education inequality between male and female users are measured based on education attainment. Other reasons for inequality identified through this study are the opportunity gap, achievement, and empowerment between men and women in India. It also explicitly denotes that India needs to improve women education.

In addition, social media analysis was also conducted in this study. Twitter sentiment analysis was carried out to prioritise the e-learning barriers or technological challenges. The technical challenges are classified into two different perspectives: organisational and social. Using the R tool, the sentiment analysis is carried out and the various emotion of online users are also analysed. Next, the user technology awareness level towards the "Digital India" scheme is measured using Twitter sentiment analysis. The two different m-learning services: civic learning and e-learning mobile apps are compared in this study. The users' perception of general learning and e-learning mobile app is analysed through Twitter analysis. The awareness level of the m-learning mobile app and the importance of the m-learning service is also explored. Apart from this, two different case studies were conducted on the platforms: mobile and cloud.

First, the quantitative analysis was carried out in a mobile-assisted learning platform for special schools. The main aim of this study was to identify various challenges faced by special students in India. The advantages of mobile-assisted learning were compared with traditional assistive technology. Through this study, it is confirmed that mobile-assisted learning provides the best platform for special students. Second, a cloud-based e-learning environment is created using the CloudAnalyst simulator tool. The efficiency of cloud-based e-learning services was measured in two different simulation set-ups: single data centre and multiple data centres. The service time and overall response time of the cloud-based e-learning service were measured. The efficiency of a cloud-based e-learning system is simulated and concludes how the cloud provides a better platform for the e-learning system. Thus, the simulation model demonstrates how cloud Infrastructure as a Service (IaaS) improves e-learning service adoption in higher education institutions.

This study provides a set of technological recommendations for the improvement of e-learning adoption. These are derived from various case studies related to e-learning adoption. The suitable e-learning architecture for the Indian higher education institutions is also suggested through this study. The implementation of this recommendation will increase the learners' adoption of e-learning. It also improves the e-learning system use and learners' satisfaction through e-learning services addressing the flexible and diverse learning community needs.

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LIST OF ABBREVIATION

ICTs	Information and Communication Technologies
HEI	Higher education institution
MOOC	Massive open online course
WWW	World wide web
IST	Information system theory
TAM	Technology Acceptance Model
UTAUT	Unified Theory of Acceptance and Use of Technology
IDT	Innovation Diffusion Theory
NPTEL	National Program on Technology Enhanced Learning
NKN	National Knowledge Network
NIC	National Informatics Centre
SQ	System quality
IQ	Information quality
SE	Service quality
CQ	Collaborative quality
PU	Perceived usefulness
UPS	User perceived satisfaction
PLS-SEM	Partial least squares - Structural Equation Modeling
VLE	Virtual classroom environment

CHAPTER 1

INTRODUCTION

Chapter 1

Introduction

This chapter starts with an overview of the study, followed by a discussion on e-learning in India, motivation and outline for the research, organization of thesis and conclusion of the chapter.

1.1 Introduction

This chapter offers a detailed background of e-learning adoption in India and is divided into seven sections. Section 1.2 introduces various definitions of e-learning, different types of e-learning, e-learning technologies and standards. Section 1.3 explains the e-learning frameworks with their dimensions, e-learning theories and information system theories. Section 1.4 addresses the relevance of e-learning in India, selected indices and the rationale for the study conducted in India. Section 1.5 discusses the motivation and methodological changes in the research. Section 1.6 describes the outline of the study, which includes the research question and objectives. The organisation of the thesis is described in section 1.7, followed by the conclusion of this chapter in section 1.8.

1.2 Background of the study

Information System (IS) is a collection of computer hardware, software programs, and other network utilities that allow users to access processed data (Berdik et al., 2021; Althonayan & Althonayan, 2017). IS also includes additional components such as data, individuals, techniques, and responses (Silver et al., 1995). Different types of IS services, such as decision support systems, knowledge management systems, healthcare information systems, and learning management systems, are built to enhance individual and organisational performance (Folorunso & Ogunseye, 2008; Althonayan & Althonayan, 2017; Agarwal & Lucas, 2005). Recently, many organisations have embraced Information Technology (IT) to manage their internal and external operations. In the education sector, The Learning Management System (LMS) is used to control learning activities, while the University Information System (UIS) is used to manage institutional administrative activities (Penalvo, 2021; Jiang et al.,2002; Hamilton & Chervany,1981). A new management framework, called the e-learning system, is implemented to handle all operations simultaneously (El-Ghareeb, 2009). In this study, E-learning is discussed from a socio-technical viewpoint (Zotov et al., 2021; Riad & Ghareed, 2007).

To design, build and sustain technology acceptance models, IS includes various theories such as the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), DeLone and McLean models (Al-Qaysi et al., 2020: Aldholay et al., 2018). Previous researchers have put forward different e-learning system models based on these information system theories to achieve learning objectives (Gunasinghe et al., 2019a; DeLone & McLean, 2003). The advancement of ICTs and the Internet has brought a modern digital learning environment that prompts education forward. Thus, E-learning is an essential paradigm in the current educational system because of the combination of IS theories and technological advancement (Islam et al., 2011).

1.2.1 What is E-learning

E-learning is a new paradigm that promotes learning and training through digital resources. The term "E-learning" was coined in 1999 by Elliott Maise at the TechLearn conference. In the late 20th century, the development of ICTs and Internet facilities enabled individuals to learn any course, anytime and anywhere (Kumar et al., 2021). Previous researchers have given different definitions for e-learning. According to Clark and Mayer (2003), e-learning defines an electronic mode of learning that accesses the educational curriculum outside of a traditional classroom. In other words, Wu et al. (2012) described e-learning as electronic learning through which information is accessed, and interactions are done among tutors and peers in the online platform. According to Choudhury and Pattnaik (2020), e-learning is well-defined content shared through media like the Internet to improve the knowledge and skillsets of the learners. Garcia-Penalvo (2021) stated that e-learning is an institution's digital transformation that interacts with stakeholders through a proper e-learning framework.

Previous studies classified the e-learning definitions into four categories: technology-driven,delivery-system-oriented,communication-oriented and educational-paradigm-oriented (Sangra et al., 2012). Guri-Rosenblit (2005) stated that e-learning uses technology to deliver learning and training through remote resources. Thus, most private companies and academic sectors highlight the technological aspects of e-learning as a primary characteristic compared to other aspects. According to the communication-oriented perspective, e-learning is defined as a communication platform through which information is exchanged between instructors and students (Bermejo, 2005; Sharma & Kitchen, 2004). As per educational-paradigm orientation, e-learning is defined as using new digital technologies to improve the quality of education through the Internet and other Information Communication Technologies (ICTs) (Wang et al., 2010). In the current study, the author defines e-learning as follows:

E-learning is a versatile online platform that uses ICTs and the Internet to deliver knowledge across geographical boundaries (Author's own).

E-learning aims to enable tutors and students to share their knowledge across geographical boundaries (Shipee & Keengwee, 2014; Alqahtani & Rajkhan, 2020). Furthermore, e-learning transforms the conventional learning environment (teacher-centric) into a student-centric platform that enhances learners' skills, problem-solving abilities, and collaborative nature (MacGregor & Turner,2009; Frederickson et al.,2005). The other terminologies used to represent e-learning are virtual learning, electronic learning, distance learning, MOOCs, and learning management systems (Aparicio et al.,2016; Berrocoso et al., 2020).

1.2.2 Types of e-learning

E-learning plays a vital role in the growth of education sector. It is essential to understand the benefits and limitations of various e-learning techniques and methods. The past studies classified e-learning into different types based on learning tools and content. Some of them are listed below:

- *Computer Management Learning (CML)*: CML provides students in the education industry with additional information such as courses, training materials, academic-related information etc. The information database stores data as computerised textbooks, simulation, and training according to the learner's needs. To retrieve data from the database, two-way communication is used between the learner and the computer. (Kellogg 1998; Whalley,1998).
- *Computer-Assisted Instruction* (CAI): The CAI or Intelligent Tutoring Systems (ITS) combines multimedia, such as text, graphics, sound and video, together to improve the teaching-learning process (Ugwuanyi & Okeke, 2020). For instance, in 1966, Stanford University used training software to interact with students (Nicholson & Nicholson, 2007). This approach aims to provide an active learning environment for the students. Both online and traditional learning methods (CAI) are used to improve students' skills and knowledge.

- *Asynchronous Online Learning:* Asynchronous online learning is a student-centric environment where the students can fix their flexible timeframes for learning. This approach uses e-mail, discussion boards, and blogs to deliver the content even when learners and instructors are not online (Shahabadi & Uplane,2015). In the online platform, the asynchronous mode is mostly used to solve complex issues. Furthermore, the students have sufficient time to comprehend and reply to the instructor (Ong et al., 2004).
- *Synchronous Online Learning:* Synchronous online learning is real-time learning in which both instructor and students are connected face-to-face through video conferencing and chat (Shahabadi et al., 2015). When the tasks are already well-planned, this mode is preferred to discuss less complex issues. In addition, synchronous online learning creates an active environment for the students to interact with instructors and other students in the online platform (Hrastinski et al., 2010). The synchronous online environment is otherwise called virtual classroom, web conference, webinars and online presentation.
- *Blended Learning:* Blended learning is a combination of asynchronous and synchronous online learning in which self-paced web-based training is followed by face-to-face instruction, and course materials are supplied in the form of text in the virtual classroom session (Wongwuttiwat & Buraphadeja, 2020). Many organisations prefer blended learning to provide online delivery through the synchronous approach and optimise face-to-face meetings through the asynchronous approach. Blended learning is an online discussion forum that includes audio, video, text, e-mail, quizzes and assignments (Wu et al., 2010; Dziuban et al., 2018).

1.2.3 E-learning technologies

E-learning is a fast-growing sector because of the development of new technologies. The ICTs and Internet combine and create a new innovative educational tool (Oloruntoyin, 2020). The emergence of e-learning technologies has changed the traditional learning environment into a student-centric and collaborative online platform. The various e-learning technologies discussed in this section are

- Text-audio presentation
- WebCT
- Web-based collaboration

- Computer-based training support tool
- Video games

Text-audio presentation

The audio was the first multimedia content delivered in the streaming format through the Internet. Text and audio are integrated to deliver content in the online environment. When the learners have poor Internet bandwidth, the text and audio presentation is considered the best way to deliver online courses. Even though it is cost-effective, many researchers argued that the text or audio alone would not provide an effective e-learning system. Because the learner's reading capacity is 300 words per minute, but the audio speed is 150 words per minute. This creates a mismatch between text and audio in the e-learning platform. Thus, many researchers suggest using only one at a time (Elekaei et al., 2020; Burin et al., 2021).

WebCT

WebCT (Course Tools) or Blackboard Learning System is the world's first successful course management system for the higher education system. The instructors can use this tool as a blackboard for presentation, discussion and live chat (Kibuku et al., 2020).

Web-based collaboration

It is a web-based application that offers instant message sharing, file sharing, integrated online calendars and Internet teleconferencing facilities. Online messages, text, audio, image and videos could be shared through Web-based collaboration tools. With the help of teleconferencing, information is shared among several users through a telecommunication system, which includes audio conferencing, telephone conferencing and/or Internet teleconferencing (Saboowala et al., 2020).

Virtual learning environment

The Virtual Learning Environment (VLE) is defined as an integrated web-based application used to share information among teachers and students through the Internet or Wide Area Network (WAN). Higher education institutions adopt VLE to enhance their teaching and learning process. The components of VLE are content management, curriculum mapping, communication and collaborative platform (Olivetti et al., 2020; Bogusevschi et al., 2020).

Computer-based training support tools

Computer-based training (CBT) is a tool used to design the learning activities by teachers or content developers based on Analysis Design Development Implementation and

Evaluation (ADDIE) model. CBT needs a personal computer or networked computer to deliver the course either in asynchronous or synchronous mode. CBT is preferred when a large group of students enrol for a course due to its cost-effectiveness (Howard & Matt, 2020).

1.2.4 E-learning standard

The e-learning standard is defined as a set of rules and guidelines to deliver the online course on any platform. With the help of e-learning standards, the content, software and Learning Management System (LMS) are developed to satisfy the stakeholder's needs. It is tested against different platforms to check interoperability. The two common standards reviewed in this study are:

- Technical Design
- Courseware Design

Technical design

It defines the guidelines to check the interoperability and portability of an e-learning system across various devices and platforms. The common technical standard followed in e-learning is SCORM, AICC, WCAG. SCORM stands for "Sharable Content Object Reference Model" and define how an e-learning system interacts with LMS to deliver the online course. It records the learner's details, including the time at which the learner accessed the course, time taken to complete the course, evaluation scores, and course completion status. AICC stands for "Aviation Industry Computer-based Training Committee". It uses HTTP messages to communicate with the LMS. WCAG stands for "Web Content Accessibility Guidelines" and is developed by World Wide Web Consortium. It explains how the online courses could be delivered in the form of web content to increase the accessibility to people with disabilities (Bohl et al., 2002; Rey-Lopez et al.,2009; Moreno et al., 2008)

Courseware Design

It includes various aspects of course design as per the customer need. The components of the course design are instructional design, visual design, media standard and assessment standard. The instructional design defines the purpose, objective, strategies, content assessment and feedback about the e-learning system. The navigation and the user-friendliness of an online portal are explained in the visual design. Next, the media standard describes the consistency and compatibility of the e-learning service across various media like text, image, animation, audio and video. The e-learning content is developed based on the end-user device, such as computer, mobile device etc. The assessment standard provides a guideline to evaluate the learners' understanding through online quizzes and tests (Sung et al., 2011; Roblyer, 1981).

1.2.5 History of E-learning

This section discusses the evolution and history of e-learning. Though e-learning gained popularity in its current form after the introduction of the Internet, its presence could be found even in the early 1900s. In 1924, students were found to be using "Test Machines" to test themselves. Similarly, Harvard professor BF Skinner invented the "Teaching Machine" to teach school students in 1954. However, the first computer-based training program was created in 1960 and was called PLATO (Programmed Logic for Automated Teaching Operations). It provided students with drills and had options to skip questions. In 1966, Computer-Aided Instructions (CAI) was implemented by Patrick Suppes and Richard C. Atkinson, who were professors from Stanford University, to teach math and reading for elementary school students.

US Department of Defense commissioned ARPANET (Advanced Research Projects Agency Network) in 1969 to create Internet and this could be considered as a major milestone in the history of e-learning. In 1970, the invention of computer mouse and Graphical User Interface had increased the acceptance and usage of computers among people. The first MAC introduced by Apple in 1980s started a new era in personal computing and thus boosted the growth of e-learning. MAC personal computers facilitated the transfer of information between its users in the comfort of their homes.

The term "digital natives" was introduced in 1990 to represent the generation born in the digital age and grown up with access to technologies such as computers and the Internet. Individuals belonging to "digital natives" showed higher usage of computers and the Internet. This generation is important in e-learning history as they had more acceptance of various technologies compared to previous generations.

In the early 1990s, certain educational institutions were established exclusively to provide online courses. It facilitated access to such courses for a large number of students who were not able to physically attend the courses due to geographical and schedule limitations. Thus, digital technologies and the Internet helped educational institutions reach a larger audience than ever before. In 1995, colleges and educational institutions had started using Learning Management System (LMS) to manage learning activities on a large scale. LMS helped the institutions to manage student records, attendance, grading etc. Later in 1999, the term "e-learning" was coined by Elliott Masie in a conference on Computer Based

Training (CBT) systems to represent how people used computers and the Internet to learn, enrol in online courses and improve their education.

At the start of twenty-first century, businesses have started utilising e-learning to train and enhance the skills of employees. The year 2001 witnessed the Massachusetts Institute of Technology (MIT) launching “OpenCourseWare project”, which provided educational content and resources freely accessible to the public and is considered to be a major milestone in e-learning history. It facilitated access to numerous courses with video content and assignments from the top professors of MIT.

The increased usage of social media platforms in the 2010s had led to the growth of social learning among individuals and students. The social media platforms (such as Facebook, Twitter, YouTube, Linked In, etc.) have enhanced the users' availability of information and educational resources. The term “Massive Open Online Courses” (MOOCs) was introduced in 2008, and MOOCs became a popular mode of learning by the year 2012.

In 2020, COVID-19 turned out to be the biggest challenge for traditional learning and gave a never-before-seen boost to the e-learning domain. People have started showing greater interest in e-learning and virtual learning platforms. This unforeseen circumstance is believed to enhance the introduction of various innovative forms of e-learning such as immersive learning, Gamification and Artificial Intelligence (AI) to the e-learning platforms. The history of e-learning is illustrated in Figure 1.1.

1.3 E-learning Frameworks

E-learning framework is defined as a conceptual model that measures system quality and learning outcomes (Shetu et al., 2021). It is necessary to ensure the quality of education globally through online mode or distance mode. Online courses should satisfy the users and fulfil the objective of the learning process. Therefore, many researchers try to find the answer to this question, “How to provide the flexible e-learning platform globally for the learners?”. Hence, the higher education funding agencies in the United Kingdom formed Joint Information System Committee (JISC) to promote the learning process through ICTs. As a part of this plan, the JISC proposed a Service-Oriented-Architecture (SOA) called e-Framework, which is fundamental for the e-learning framework (Wills et al., 2009).

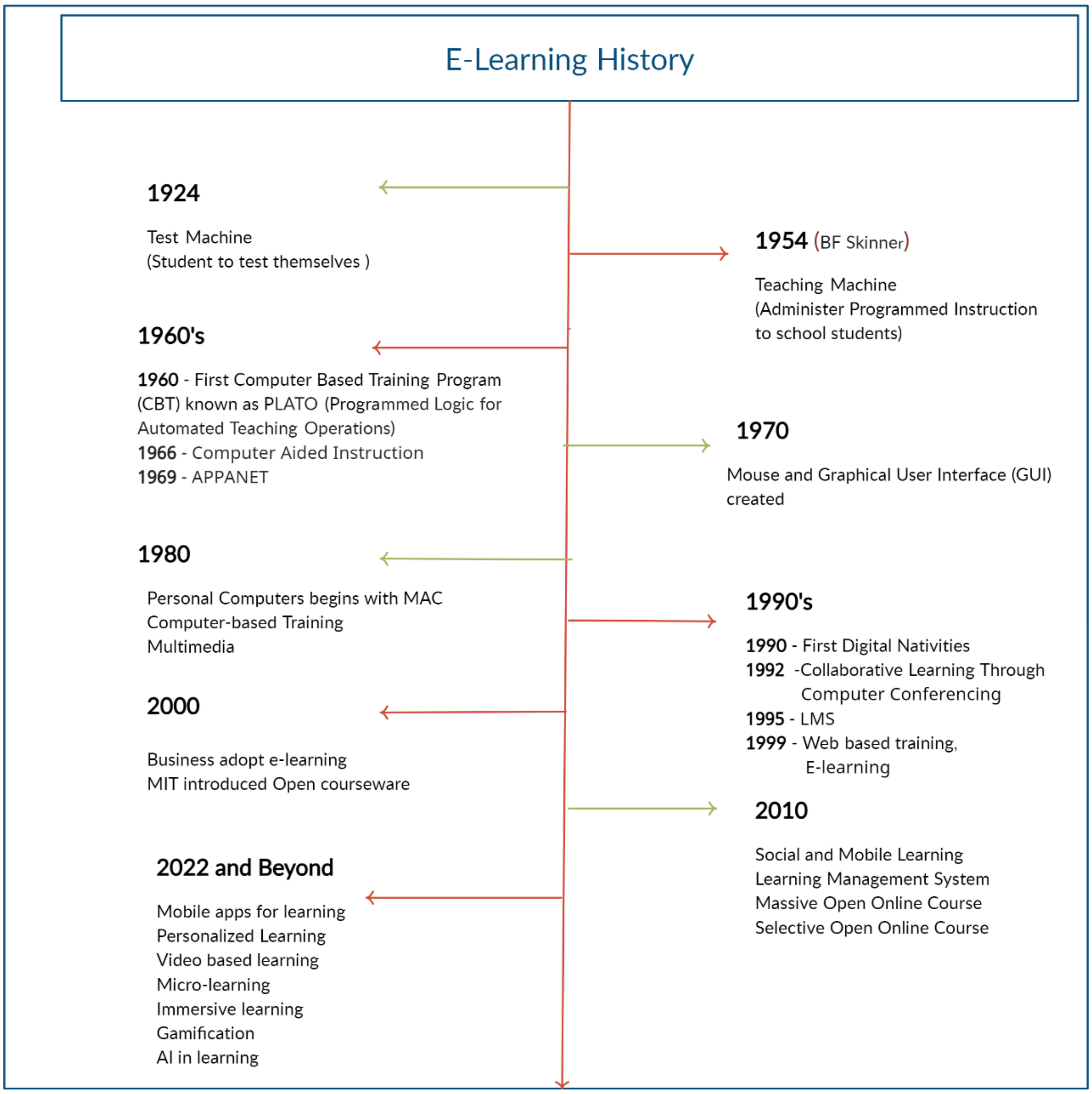


Figure 1.1: E-learning History

On the other hand, Khan (2004) developed a model with input from numerous stakeholders, and it included the People, Process, and Products (P3) Continuum to enhance e-learning. This e-learning framework mainly focused on the instructional system design and pedagogical factors of the online learning environment. Based on these factors, Khan developed the Comprehensive Approach to Program Evaluations in Open and Distributed Learning (CAPEODL Model) in 2002 and adopted it by Federal Leadership Institution in the USA. The framework is divided into multiple dimensions based on functionality. To quantify e-learning outcomes, each dimension has its own set of properties. The eight dimensions suggested in the e-learning framework by Badrul Khan are Pedagogical, Technological, Managerial, Interface design, Resource support, Evaluation, Ethical, and Institutional (Khan & Joshi, 2006).

Sun et al. (2018) developed an integrated e-learning model to examine the relationship between the factors in the e-learning environment. The critical factors that affect learners' satisfaction in the online environment are analysed using six dimensions: user/learner, instructor, pedagogy, technology, design, and environmental. In this study, the dimensions of the e-learning framework are developed based on previous researches. The various dimensions adopted in the study is shown in Table 2.1.

Table 1.1 Dimensions in E-learning Framework

Authors	E-learning dimensions	Description
Arbaugh (2000); Arbaugh (2002)	Learner	Learner's attitude towards e-learning adoption
Piccolo et al. (2001); Sun et al. (2008)	Technological	The technological quality and Internet quality, which includes reliable service and Internet speed, are analysed in the technological dimension
Stoffregen et al. (2015) Abhiyendra (2007); Pearce and Rice (2013)	Barrier	It is used to analyse the technological and individual barriers that learners face during e-learning adoption.
Wills et al. (2009); Khan (2004)	Institutional	The administrative and academic activities as well as student support provided by the institution.
Khan (2004); Khan and Joshi (2006)	Management	It provides and maintains the platforms where the knowledge is shared among users
Sun et al. (2008); Arbaugh (2000)	Design	E-learning usage and learner's satisfaction is measured in the design dimension.
Khan and Joshi (2006); Jung (2011); Govindasamy (2002)	Pedagogical	Awareness and performance of different types of users are studied under audience analysis

The factors that influence e-learning adoption were analysed under the technological and learner dimension. Learner, technology, design, pedagogy dimensions are adopted from Sun et al. (2008) and Arbaugh (2002). The management dimension is adopted from Ozkan and Koseler (2009) and Khan and Joshi (2006). The institutional dimension and barrier dimension are taken from Stoffregen et al. (2015) and Pearce and Rice (2013). The pedagogical dimension is taken from Khan (2001) and Jung (2011). In addition, this study also identifies the factors that influence e-learning adoption based on gender using theories pertinent to gender difference.

1.3.1 E-learning Theories

Learning theories are conceptual frameworks that define the way individuals acquire and retain knowledge. According to Evgeniou and Loizou (2012), e-learning combines various educational theories from cognitivism, behaviourism and constructivism. In this study, four different learning theories determine the learner dimension in the e-learning framework.

Cognitivism

Cognitivist theories are used as a basis in modern education. Through cognitivism, Bereiter (1990) established the international learning model to solve learning difficulties. According to Piaget (2009), the most influential aspects of e-learning are the learners' internal and external experiences. Therefore, the cognitivism model analyses how the learners process knowledge and connect it to previously learned information. Many researchers confirmed that the learner's ability would be enhanced by prior knowledge about the courses (Jacobsen, 2019; Jeong Kim et al., 2012; Pritchard & Woollard, 2010). As a result, the cognitivist technique was used in this study to evaluate the learners' understanding and learning capability (Evgeniou & Loizou, 2012).

Behaviourism

Behaviourism is the oldest learning theory according to which a learner's stimuli will react immediately without any thought process. It is essential to develop the instruction design to achieve a better learning outcome. According to Evgeniou and Loizou (2012), behaviourism is defined as a change in learners' behaviour after the teaching-learning process. The past studies also confirm that the learning environment would develop according to the learner's need so as to achieve the learning objective (Skinner, 1971; Bereiter, 1990; Iskander et al., 2014). Therefore, the learning environment is considered as one of the critical factors in learning theories.

Constructivism

Constructivism is one of the learning theories used to interlink the learning environment with users' post-cognitive skills. Each user can build their own knowledge based on experience and recent events. It also encourages the users to participate in the group discussion with the instructor and peers (Connaly & Begg, 2006; Cornu & Peters, 2005). This theory is sub-divided into two categories: cognitive constructivism and social constructivism. The former represents the users' individual characteristics and later express the users' social behaviour (Talja et al., 2005). Based on constructivism theory, the user's individual behaviour and social behaviour are analysed.

Feminist theory

The feminist theory is developed to understand gender inequality based on social roles, interests, individual characteristics and experience in various domains (Brabeck et al., 1997; Limerick & O'Leary, 2006). This study includes the feminist theory to analyse gender inequality in the education domain. This study uses theories to measure the individual and social factors that affect e-learning adoption based on gender differences. The level of individual performance and achievements is measured based on the gender gap. External factors, including the individual's behaviour and attitude, are considered as critical factors in gender theory (Van Hek et al., 2015; Bendl & Schmidt, 2012). In addition, perceived satisfaction and technology awareness are also included as additional factors in this study. The primary purpose of using these factors is to strengthen the research model.

1.3.2 Information system theories

IS theories and models are based on a variety of variables that have been discovered by empirical evidence. The acceptance of technology by users in various domains is measured by IS theories (Gunasinghe et al., 2019b). IS theories connect system theory with information technologies. The primary purpose of IS theories is to validate the information system model for a particular objective (Chen & Tseng, 2012). Over the past 45 years, research has been conducted to evaluate the factors that affect technology adoption at the individual and organisational levels. As a result, several theories have been formulated and used to decide if a specific technology would be accepted or rejected in the field of information systems (Tarhini et al., 2015; Venkatesh et al., 2012).

Previous researchers developed technology acceptance models such as "Social Cognitive Theory" (1960), "Theory of Reasoned Action" (Ajzen & Fishbein, 1975), "Diffusion of Innovation Theory" (Rogers, 1983), "Keller's Motivation Model" (1983), "Theory of Planned Behavior" (Ajzen, 1985), "Technology Acceptance Model (TAM)" (Davis, 1989), "Model of DC utilisation" (1991), "Motivation Model" (1992), "DeLone and McLean Information Systems Success Model (DMISM)" (1992), "Theory of Technology Fit" (Goodhue, 1998), "Unified Theory of Acceptance and Use of Technology (UTAUT) - 1" (Venkatesh et al., 2003), "Updated DeLone and McLean IS Success Model" (2003), "UTAUT-2" (Venkatesh et al., 2012), "UTAUT-3" (2017), to measure technology acceptance (Al-Qaysi, 2020; Gunasinghe et al., 2019a; Delone & McLean, 2003; Gergor, 2002; Ray et al., 2019; Shim et al., 2018). Each theory has different dimensions to validate its models. However, only a few studies combine these models and validate the research. The current study uses the TAM, DeLone and McLean IS success model, Updated DeLone and McLean IS success model, and Diffusion of Innovation Theory to frame the e-learning adoption model.

Keller's Motivation Model

Keller (1987a) developed the ARCS model (Attention, Relevance, Confidence, Satisfaction) to explore learner motivation and incorporate the learning environment techniques. Many researchers identified that motivation is the fundamental factor determining a student's academic performance (Anderman & Maehr, 1994; Ames, 1992). The primary goal of the motivational model is to identify the need of the learners and to provide a learning system according to the learner's experience. In addition, opportunity is given to learners to encourage their activities in the learning environment. Hence, the motivational model is designed similar to the traditional model to satisfy the learner's need (Keller 1987b, Klein & Keller 1990; Sankaran & Bui 2001; Huang et al., 2006).

Huang et al. (2006) adopt the ARCS model to evaluate the motivation level of users in higher education. Huang et al. (2006) modified the motivation model related to the higher education system to predict how the learner reacts in an online environment. This study examines two distinct motivation styles, intrinsic motivation and extrinsic motivation, as perceived satisfaction and perceived usefulness, respectively (Cidral et al., 2018; Sun et al., 2008). From an e-learning perspective, the learner's motivation and engagement are critical in implementing emerging technologies (Liaw & Huang, 2013).

Technology Acceptance Model

Technology Acceptance Model (TAM) is an information system framework used to analyse technology acceptance and user adoption in workplace environment. TAM model also analyses the process of technology acceptance by an individual. The factors that influence technology acceptance are analysed in this model (Davis et al., 1992; Fakhoury & Aubert, 2017). TAM model was derived from the Theory of Reason Action (TRA) model (Napitupulu et al., 2017; Venkatesh, 2002). Hence, many empirical studies have used the TAM model to evaluate user technology acceptance in various domains (Wu & Chen, 2017; Teo et al., 2009).

According to King and He (2006), TAM could be used to validate the system's performance in the learning environment. Previous researchers have used the original TAM model and extended it by adding additional constructs (Liaw, 2008; Sun et al., 2008). The benefits of technology acceptance are validated with TAM by using external variables such as individual characteristics, system characteristics, and social influence (Portz et al., 2019). Hence, this study utilised the TAM model to assess e-learning adoption using system characteristics and learners' characteristics (Chang & Tung 2008; Arbaugh 2002).

DeLone and McLean Models

In 1980, Peter Keen pointed out a lack of research in information theory, and he argued that there was no standard dependent variable for IS success theories. To solve this issue, DeLone and McLean Model (1992) contributed their first IS success model. According to the DeLone and McLean Model, the framework is subdivided into six dimensions: system quality, information quality, use, user satisfaction, individual impact and organisational impact. More dimensions were added as an extension of the DeLone and McLean model, and an updated DeLone and McLean Information System (DMIS) model was proposed (DeLone & McLean, 2003, 2004). The additional dimensions included in the updated DMIS are service quality, intention to use and net benefits. The system characteristics are evaluated using system quality, information quality and service quality.

Meanwhile, user satisfaction and intention are used as mediator variables in the IS system model (Urbrach & Mulller, 2012). The updated DMIS does not show the positive or negative signs associated with success dimensions (DeLone & McLean, 2003). Feedback loops were used to validate the relationship between use, user satisfaction and net benefit in the updated DMIS model. Many researchers utilised the updated DMIS model to measure user satisfaction in the online environment (Bin Masret, 2007).

Diffusion of Innovation Theory

The Diffusion of Innovation Theory (DOI) attempts to decide whether users of information systems accept or reject innovation. The term “innovation” refers to new ideas that a person or organisation perceives, while “diffusion” refers to how new ideas are conveyed to users over time through the appropriate medium (Ullah et al., 2021; Agarwal, 2000). DOI is an information system theory that supports implementing an e-learning system by combining it with other theories. Roger’s DOI is divided into five phases as diffusion stages for new technology adoption: awareness, interest, evaluation, trial, and acceptance or rejection (Agarwal et al., 2000; Rogers, 1995). In this study, the final stage of the DOI process, “acceptance”, is added to the conceptual model as a construct (e-learning adoption).

1.4 E-learning in India

United Nations (UN) Sustainable Development Goals promote digital education through the ProFuturo project, UN agencies, Government, and other telecommunication industries under Sustainable Development Goal 4 (SDG4 2017). The purpose of this United Nations Development Programme (SDG4) is to provide affordable, reliable, and contextsensitive digital education across the world. It further aims to make better use of information technologies and increase fundamental skills like collaboration and users' problem-solving skills. Digital education technologies may connect users from different parts of the country without gender inequality.

In line with SDG4, Sarva Shiksha Abhiyan has been introduced in India to achieve global quality in higher education. By 2020, substantially expanding scholarships for developing countries like India will encourage enrollment of students in higher education. It will also improve the quality of teachers through international cooperation in teacher training among developing countries by 2030. However, as per reports (PRS, 2016), the integration of ICTs in the education sector is inadequate in the Indian education system. It also recommended the use of ICTs for teacher training, digital literacy, and learning tools in higher education. The G20 Framework for Strong, Sustainable and Balanced Growth (2018) defined reform priorities for each country. Easy access to the resources and quality of the education system are considered as top priorities among the five priorities for India (OCED 2018, India). Thus, the new National Education Policy and Sustainable Development Goal 4 tries to bridge the digital inequality in the teaching-learning process.

According to the Indian Brand Equity Foundation (IBEF) report (2018), India has one of the largest higher education systems in the world, with 28.1% of the Indian population between 0-14 years age group and 260 million students enrolled in 1.5 million schools, 751 universities, and 35,539 colleges. In 2016-17, the total number of students enrolled in higher education was 35.7 million. A report by E-learning Market Global Outlook and Forecast 2018−2023 showed that the e-learning market size was expected to grow by 7.07% (CAGR) and was estimated to reach $65.41 billion in the year 2023. This will be due to the growth of mobile users and the development of social media learning.

According to KPMG (2017) report, the e-learning industry is broadly classified into two main categories as content and technology-related services. The development in technology and responsiveness of the users are considered as key for future growth. It also estimated the growth of e-learning to be $1.28 billion at the end of the year 2018. Finally, the Internet penetration in India had significantly increased to 31% in the year 2016 and was expected to grow from 409 million Internet users to 735 million by 2021. The development of the Internet was also reflected in the massive growth of e-learning in higher education. The online education market in India was $247 million in 2016, with approximately 1.57 million paid users. It is estimated to increase to $1.96 billion for the next five years due to better customer adoption support and improvement in the business model. In the online education market, the market size of higher education was 13% out of the total market size. According to the Organization for Economic Co-operation and Development (OECD 2018) report, Indian policymakers focus on providing quality education. As an initiative process, the Programme for International Student Assessment (PISA) was conducted in India's two states of Himachal Pradesh and Tamil Nadu. Through PISA, Indian policymakers identified factors associated with students' usage and outcome to bridge the gap across socioeconomic groups (Siriginidi, 2005).

1.4.1 Indices of India's digital environment

According to Global Competitiveness Index report (2019), India stabilised in 68^{th} place after its giant leap forward in the previous two years. The score improved across most factors of competitiveness, particularly infrastructure, higher education and training, and technological readiness, reflecting recent public investments in these areas. Although the technology is improving, technological barriers still exist in India and reduce e-learning usage.

Various pillars and variables were used to assess selected instances in India's digital ecosystem. These pillars and variables are seen as critical aspects for the long-term growth of higher education. This study identifies the index values associated with numerous dimensions and factors. It also analyses the digital environment's growth rate over a five-year period from 2014 to 2018. The key objective of the selected indices is to determine India's current status in terms of digital growth. The rankings/scores represent the rate at which digital resources are evolving. Table 1.2 has a thorough report on the selected indices that measure the digital status.

Table 1.2: Select indices of India's digital environment

Index and source	Pillars	Factors	India's rank/Scores					Remarks about India
			2018	2017	2016	2015	2014	
Global Competitiveness Index *(Source: World Economic Forum, International Telecommunication Union, World Telecommunication/ICT Indicators)* .	Overall rank		40	39	55	71	60	India (40^{th} rank) stabilised in 2018, after its giant leap forward of the previous two years. The score improves across most factors of competitiveness, particularly infrastructure (66^{th}, up two), higher education and training (75^{th}, up six), and technological readiness (107^{th}, up three), reflecting recent public investments in these areas.
	Institutes	Overall	39	42	60	70	72	
		Efficiency of government spending	20	50	51	49	87	
		Transparency of government policymaking	50	51	58	64	61	
		Reliability of police services	62	53	86	88	82	
	ICTs access	Infrastructure	66	68	81	87	85	
		Fixed-telephone lines/100 pop.*	111	114	116	118	118	
		Mobile telephone subscriptions/100 pop.*	110	123	121	121	123	

	ICTs skills	Higher education and training	75	81	90	93	91	ICTs usage improved (107th rank) compared to previous years. The report shows that ICT indicators include Internet bandwidth per user, mobile phone and broadband subscriptions, and Internet access in the education sector.
		Tertiary education enrollment rate	88	93	86	87	98	
		Quality of the education system	26	29	43	45	33	
	ICTs use	Technological readiness	107	110	120	121	98	
		Availability of latest technologies	72	78	108	110	58	
		Internet user's % pop.	100	102	107	115	120	
		Fixed-broadband Internet subscriptions /100 pop.	105	106	104	103	106	
		Internet bandwidth kb/s per user	102	117	116	107	113	
		Mobile-broadband subscriptions /100 pop.	124	127	124	114	99	
	Barriers problematic factors (out of 30)	Corruption	9.2	10.9	10.1	8.0	17.3	According to the report (2018), the quality of institutions has increased, especially in terms of the efficiency of public spending (20th). However, the private sector still considers corruption to be the most problematic factor. It is also identified that inadequate infrastructure and an uneducated workforce are other barriers to doing business in India.
		Inadequate supply of infrastructure	7.0	2.5	7.3	8.1	18.1	
		Poor work ethic in national labor force	7.0	6.0	1.5	4.7	3.0	
		Inadequately educated workforce	6.6	2.5	5.5	6.3	2.2	
		Government instability/coups	6.6	5.7	7.3	6.4	2.8	
		Insufficient capacity to innovate	4.7	7.3	6.1	3.8	2.8	
		Policy instability	4.3	3.6	9.6	4.8	6.6	
Global Innovation Index *Source: Cornell University, INSEAD, and the World Intellectual Property Organization (WIPO)*	Overall rank		57	60	87	81	76	India was ranked 57th among 130 countries. The indicators that have helped improve India's ranking are Information and Communication Technology (ICT) and services.
	Infrastructure	Overall	77	73	87	87	87	
		ICT access	105	106	108	115	111	
		ICT use	110	109	107	117	112	
		Government's online service	33	33	57	57	56	
		E-participation	27	27	40	94	73	
	Business sophistication	overall	64	55	57	116	93	The 2018 report shows that India has fared badly on indicators such as ease of starting business, political stability/safety, overall education and environmental performance.
		Knowledge absorption	66	55	66	99	100	
		Communication, computer & information services implementation % total trade / ICT services imports, % total trade	66	78	70	74	75	
	Knowledge & technology outputs		43	38	43	49	50	
		Knowledge impact	42	30	48	84	87	
		Computer software spending	65	66	62	68	74	
	Innovation linkages		41	37	43	52	46	
		University/industry research collaboration	25	23	49	48	43	
Network readiness index *(Source: Geneva-based World Economic Forum, Global Information Technology Report)*	Overall rank		-	-	91	89	83	India has scored better in terms of political and regulatory environment (78th position). It ranked very high (8th place) in terms of affordability, 57th place in online services and 40th place in allowing e-participation. It scored worse in terms of business and innovation
	Usage	Overall	-	-	103	103	91	
		Individual usage	-	-	120	121	121	
		Government usage	-	-	75	88	51	
		Business usage	-	-	59	62	41	
	Readiness	Overall	-	-	88	83	85	
		Infrastructure and digital content	-	-	114	115	119	
		Affordability	-	-	8	1	1	
		Skills	-	-	101	102	101	
	Impact	Overall	-	-	73	73	60	

		Economic	-	-	80	92	50	environment (110th). It scored worse in infrastructure facilities (114th) place. India also fares poorly on sub-indices for levels of skills (101st) and individual usage (120th).
		Social	-	-	69	68	73	
	Government usage	Government online services	-	-	57	57	55	
		Government success in ICT promotion	-	-	75		29	
	Social impacts	e-participation	-	-	40	40	72	
Change readiness index *(Source: KPMG International corporative report)*	Overall rank	-	-	64	-	67	-	India ranked 53 in Government capability, which includes the ability of governmental and public regulatory institutions to manage and influence change. Also, it is in the 88th place in people and civil society to adopt the change and respond to opportunities.
		Government capability	-	53	-	69	-	
		People and civil society capability	-	88	-	83	-	
ICTs Development Index (IDI) *(Source: International Telecommunication Union)*	Overall rank		-	134	138	131	-	India ranked 134 in ICTs Development in the year 2017. ICTs usage is low (144th rank in 2017) compared to the previous year (142 in 2016). It indicates that India is suffering from the digital divide problem.
		IDI access	-	137	139	135	130	
		IDI use	-	144	142	135	-	
		IDI skill	-	121	124	120	-	
Digital competitiveness index *(Source: International Institute for Management Development (IMD) world digital competitiveness report)*		Digital competitiveness index (overall)	48	51	53	50	56	India has climbed to the 48th position on the 2018 IMD World Digital Competitiveness Rankings, improving three places over last year.
	Knowledge	Overall	46	37	39	37	39	
		Talent	43	43	38	39	36	
		Training and education	59	47	56	45	56	
		Scientific concentration	26	6	21	21	21	
	Technology	Overall	53	59	57	58	57	
		Regulatory framework	56	59	56	59	59	
		Capital	3	28	30	34	28	
		Technological framework	62	63	61	61	60	
	Future readiness	Overall	48	51	54	53	57	
		Adaptive attitudes	54	59	57	56	60	
		Business agility	33	29	35	37	41	
		IT integration	56	56	54	53	56	
Inclusive Internet Index *(Source: The Economist Intelligent unit report)*	Overall rank		47	36	-	-	-	India ranked 47th out of 86 countries in the Inclusive Internet Index (III) 2018 report. India has slipped by 11 positions compared to the previous year, 2017 (36th rank). Indicators like Internet inclusion, network coverage and pricing, e-inclusion policies, availability of local-language content were identified to be less supportive for the development.
		Availability	62	46	-	-	-	
		Affordability	39	26	-	-	-	
		Relevance	37	36	-	-	-	
		Readiness	23	25	-	-	-	
Education Index - Human Development (HDI) report *(Source: United Nations Development Programme)*	-	-	130	131	131	130	135	India ranked 130 on the 2018 (HDI), which shows improvement over the years. It indicates the development in equal distribution of outcomes in education, life expectancy, and income within the country.

Corruption perception index *(Source: Transparency International Report)*	-	-	-	81	79	76	85	India has been ranked 81 among 180 countries. It singled out India as one of the 'worst offenders' in the Asia-Pacific region.

This study identifies digital technology adoption based on knowledge, technology, and future readiness. Furthermore, it examines the many elements and sub-factors that influence digital technology adoption in terms of Government, society, and business model. It also compares the rankings and scores for five years, from 2014 to 2018. According to the indexes, India's digital environment is comparably high for the current year compared to prior years. It clearly states that the Indian Government's policies and framework strengthen the digital environment.

Table 1.3: Adoption of digital technologies in India (Government, society, and business model).

Dimensions	Factors	Sub factors	Rank/Scores					Remarks
			2018	2017	2016	2015	2014	
Knowledge *(Source: IMD world digital competitive ness report)*	Overall		46	37	39	37	39	As per 2018 report, the knowledge dimension decreased from 37th place to 46th place, indicating that talent level, and quality of education and training are less than previous years.
	Talent	Educational assessment PISA - Math	-	-	-	-	-	
		Digital/Technological skills	32	28	-	-	-	
	Training and education	Total public expenditure on education	59	58	-	-	-	
		Higher education achievement	58	53	-	-	-	
		Pupil-teacher ratio (tertiary education)	55	48	-	-	-	
	Scientific concentrati on	Total expenditure on R&D (%)	47	40	-	-	-	
		Total R&D personnel per capita	55	-	-	-	-	
		Scientific and technical employment	-	-	-	-	-	
		High-tech patent grants	7	11	-	-	-	
Technology *(Source: IMD world digital competitive ness report)*	Regulatory framework	Overall	53	59	57	58		India's score (53rd position in 2018) shows that digital technologies are developing. It also indicates the improvement in technological framework, supporting regulatory environment and capital to invest in technology.
		Development and app. of technology	35	29	-	-	-	
		Scientific research legislation	35	42	-	-	-	
	Capital	IT & media stock market capitalization	14	8	-	-	-	
		Funding for technological development	37	34	-	-	-	
		Investment in Telecommunications	1	42	-	-	-	
	Technologi cal framework	Communications technology	48	43	-	-	-	
		Mobile Broadband subscribers	63	62	-	-	-	
		Wireless broadband	62	61	-	-	-	
		Internet users	63	61	-	-	-	
		Internet bandwidth speed	57	58	-	-	-	
		High-tech exports (%)	51	45	-	-	-	
Future Readiness *(Source: IMD world digital competitive ness report)*	Adaptive attitudes	Overall	48	51	54	53	57	Report (2018) indicates that India got the 48th position in Future Readiness to exploit digital transformation. It shows that the adoption of new technologies is high compared to the previous years.
		E-Participation	23	23	-	-	-	
		Internet retailing	52	52	-	-	-	
		Tablet possession	61	59	-	-	-	
		Smartphone possession	58	60	-	-	-	
		Attitudes toward globalization	20	14	-	-	-	
	Business agility	Use of big data and analytics	19	22	-	-	-	
		Knowledge transfer	42	44	-	-	-	
	IT integration	E-Government	60	60	-	-	-	
		Public-private partnerships	34	26	-	-	-	
		Cyber security	46	47	-	-	-	
		Software piracy	48	48	-	-	-	

1.4.2 Government Initiatives

The Indian Government introduced many initiatives programs like “Digital India”, which has led to the massive growth of ICTs. For instance, the Government promotes digital awareness programs among school and higher education students through the “Digital India campaign” (Nedungadi et al., 2019). It increases the digital literacy rate and encourages users to take online courses (Bharucha, 2019). According to the National Board of Accreditation report, many universities prefer to provide e-learning courses to fill this gap. Hence, Indian higher education institutions are willing to adopt e-learning (Hemant & Manohar 2016; Bliuc, Goodyear & Ellis, 2007; Ellis et al., 2009; Garcia et al., 2018; Reeves, 2000).

As per the University Grant Commission Act, the number of educational institutions is increased. Totally 1031 engineering colleges are present in India, including centrally funded technical institutions (Gulzar & Leema, 2016). The rapid development of educational institutions requires more manpower and technical resources. Moreover, the substantial technological growth within a short time period creates a knowledge gap among instructors and users. This increases the demand for qualified instructors and experts in the education sector. Thus, it creates a shortage of faculties and other educational resources in higher education institutions (Nneka Eke, 2010).

1.5 Motivation for the study

Advancements in information technology and communications, especially in the education sector, have transformed the way services are delivered around the world today. People used to communicate and share information using desktop computers and laptops. But they now focus on mobile phones and Personal Digital Assistants (PDAs), which are more digitally capable devices. The population is migrating from traditional learning to online learning, as seen in Figure 1.2, and this is affecting total Internet usage, which has also increased from year to year.

As a result, there is a need to address the educational issues that developing countries like India face, such as lack of digital resources, unequal distribution of digital resources, learners’ attitudes toward e-learning, and skilled instructors’ shortage. Considering this, the current study is carried out to bridge the gap between digital resources and learners; and to address factors connected to e-learning adoption and the population of learners.

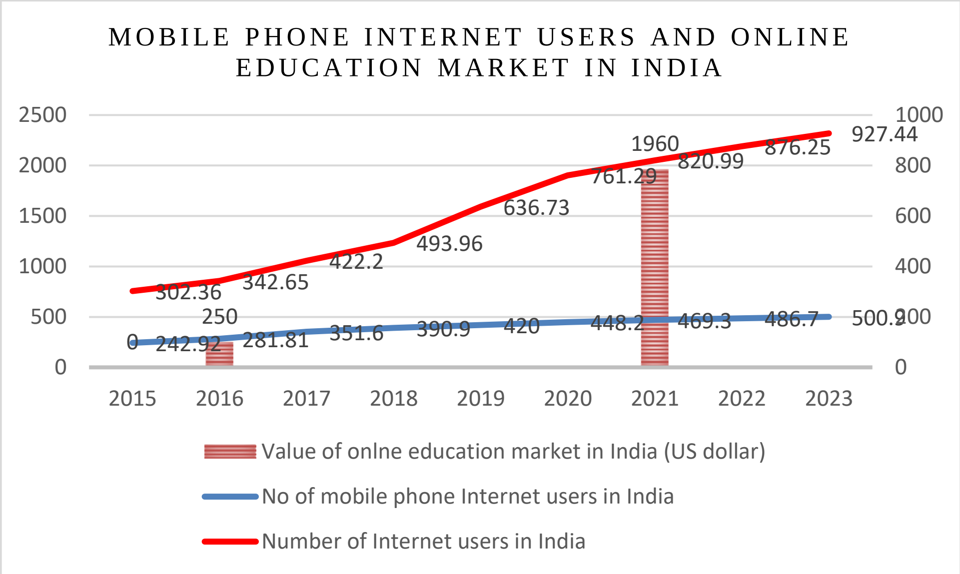


Figure 1.2: Mobile Phone Internet Users and Online Education Market in India *(Source: Authors' own)*

1.6 Outline of the study

Because of Information and Communication Technologies (ICT) and Internet use, the value of education has grown for people worldwide during the past several decades. The inclusion of "Quality Education" as one of the United Nations' primary sustainable development goals places a strong emphasis on adult education as well as technological and pedagogical advancements in teaching and learning. Learning is made easier using mobile platforms. For example, E-learning platforms such as Coursera, Udemy, Udacity, and edX have a combined user base of over 20 million people.

In the global education business, India is a major player and has one of the world's largest networks of higher education institutions. On the other hand, there is still a lot of opportunity for development in the educational system. With 26.31 per cent of India's population between the ages of 0 and 14, the country's academic industry has enormous growth potential. The Indian Government has created several free e-Learning portals for students in many fields. The purpose of free e-Learning platforms is to maintain consistent learning and teaching process. To resolve the current COVID-19 problem, the Indian

Government has taken several steps through the Ministry of Education and the University Grants Commission.

Therefore, this research tries to explore and find answers to the following research question: *How to improve e-learning adoption in the Indian context?*

The following research objectives have been developed based on the research question to guide the study design, data collection, and data analysis.

Research Objective 1: To study the factors that influence e-learning adoption.
Research Objective 2: To identify the e-learning implementation barriers in the Indian context
Research Objective 3: To analyse the e-learning platform with case studies of existing Initiatives
Research Objective 4: To bring out recommendations for improving e-learning adoption.
Research Objective 5: To develop an e-learning framework to improve e-learning adoption in the Indian context.

These research objectives will drive through various e-learning dimensions and factors to give an appropriate e-learning framework and increase e-learning adoption in the Indian context.

1.7 Structure of the report

This study consists of seven chapters, and each of them addresses a critical issue of the research as follows:

Chapter 1: Introduction to the Research Area

Chapter 1 has introduced the main issues this research will address, focusing on the e-learning framework that would influence the adoption of e-learning in India. It has given a brief introduction to the research area, and different definitions of e-learning were acknowledged. Further, a brief history of e-learning, different types of e-learning, technologies and standards were presented. Various e-learning frameworks and e-learning in India have been discussed. This chapter also outlined the motivation for the study, followed by a summary of the study's structure and a brief description of each chapter.

Chapter 2: Literature Review – Critical Analysis of the Research Area

Chapter 2 will review and examine the existing literature and studies on e-learning, highlighting the research problem and identifying the main factors that influence the adoption of e-learning in general and specifically in India. After that, a detailed discussion on the barriers to e-learning adoption will be conducted to identify the most influential factors that would hinder the adoption of e-learning. Also, the main barriers of e-learning adoption in India will be compared with those found in developed countries, exploring and distinguishing the priorities of different societies. Special education is reviewed under various disabilities, and the factors that influence special education is identified. Finally, this chapter gives a presentation of the main models and theories that have been developed and adopted when estimating and describing the implementation, acceptance, and adoption of new technologies by individuals.

Chapter 3: Research Design and Methodology

Chapter 2 sets the background for this research and identifies the research issues. To undertake the research that focuses on these issues, an appropriate and comprehensive research methodology must be followed. This chapter explains the overall research design process and justification for the chosen research methods. It starts by describing different philosophical approaches and strategies in the field of Information Systems, justifying the chosen methods. Then, the chapter discusses the data collection methods and protocols used in different studies conducted in this research. After that, the data analysis methods used in this research were explained and discussed. The chapter then concludes by explaining the ethical considerations that were followed when conducting this research.

Chapter 4: Quantitative Research Analysis

This chapter analyses and discusses the quantitative study findings of the initial conceptual model proposed in Chapter 4, considering e-learning adoption from an institution perspective in India. The quantitative study was conducted through a questionnaire-based survey to investigate the factors that influence the adoption of e-learning. The chapter provides descriptive statistics of the data collected from the participants in higher educational institutions in India. Also, it will assess the adequacy of the model through measurement model analysis and structural model analysis by using structural equation modelling. After that, the chapter discusses the implications of the survey's findings and summarises the major results and findings. Finally, the chapter will conclude by testing the proposed hypotheses and revising the conceptual model based on the survey outcomes.

Chapter 5: Qualitative Research Analysis

This chapter analyses and discusses the qualitative study findings of the initial conceptual model proposed and the survey outcomes. The qualitative study was conducted through semi-structured interviews to search for more details and investigate the factors that influence the adoption of e-learning in the context of India. The qualitative analysis was used to confirm this research's previous findings and explain the unexpected findings. The chapter will explore and study the relationships between the conceptual model's constructs explained in Chapter 3. The chapter starts with identifying and explaining the themes developed. Then, the interviews will be analysed based on the themes developed. Subsequently, findings from the interviews will be discussed, and the important factors influencing the adoption of e-learning will be identified. This chapter will conclude by presenting a final revised conceptual model based on this research's findings.

Chapter 6: Synthesis of the Study

This chapter synthesises the empirical findings with the literature. It revises the proposed conceptual model based on the factors found to most influence e-learning adoption in India. Also, it will consider factors that were emerged in this research and were not included in the original conceptual model. The e-learning adoption framework was presented for Indian users based on the quantitative and qualitative research findings.

Chapter 7: Conclusions and Further Research

Finally, this chapter will summarise and draw conclusions based on the study's final results, implications for research and practice, limitations, and recommendations for future research.

1.8 Conclusion

This study put forward that there is a lack of prior research investigating e-learning adoption in developing countries and applying theoretical models in the context of e-learning adoption. To understand and improve the adoption of e-learning, this research will propose a conceptual model based on the well-established e-learning adoption models and is motivated by an exploratory study conducted at the beginning of this research. To that purpose, this chapter gave an overview of the study's subject as well as the research's background. It also stated the research's purpose, aims, and importance. The next chapter examines the literature that this study is based on.

CHAPTER 2

LITERATURE REVIEW

Chapter 2

Literature review

2.1 Introduction

This chapter discusses the theoretical background, empirical background and identification of research gaps that are structured as follows. Section 2.2 reviews literature published on factors influencing e-learning adoption. Section 2.3 discusses gender-based e-learning adoption based on selected country studies. The e-learning barrier factors are explained in section 2.4. Section 2.5 explains various case studies related to e-learning platforms, including mobile apps in special education, mobile-assisted e-learning services and cloud-based e-learning system, followed by research gaps in section 2.6. Finally, this chapter ends with a conclusion in section 2.7.

2.2 Factors influencing e-learning adoption

In the era of electronic learning 3.0, existing dimensions related to technologies and learners are not adequately explored while discussing e-learning adoption. Literature review revealed that less adequate studies were reported for e-learning adoption. Particularly, only few articles combine two or more IS theories to measure e-learning adoption (Sun et al., 2008; Portz et al., 2019; Wu & Chen, 2017; Urbrach & Mulller, 2012; Chan et al., 2021; Lopez-Belmonte et al., 2021). In addition, very few studies combine learning theories to measure learner characteristics in the online environment and less studies have been conducted on learning theories in India (Wang & Chiu, 2011; Cidral et al., 2018; Kapoor et al., 2014; George et al., 2014; Daultani et al., 2021; Asvial et al., 2021).

In this study, technology and learner dimensions are converged to overcome this insufficiency in analysing e-learning adoption. Earlier studies have reported less about e-learning adoption in higher education through the users' lens. System parameters and learner attributes were derived from theories of information systems and literature on learning theories.

E-learning is defined as distance education provided through the technology platform. A virtual environment is set up through technology support (Chang, 2016; Lim et al., 2007). E-learning is the new dimension to improve the education domain with latest technology (Shehzadi et al., 2020). It interconnects rural students with experts all over the world. The purpose of e-learning is to provide quality education and reduce the knowledge gap. E-learning is known for transforming knowledge through a network-enabled digital device (Bisht et al., 2020). The ICTs are creating a virtual environment set-up for in and out of the classroom, with the Internet as well as sources like images and streaming videos (Andersson & Hatakka, 2010; Kodama, 2001; Parikh & Verma, 2002). In recent years, the advancement in the Internet and multimedia technologies has improved the e-learning system and quality (Fryer & Bovee, 2016; Hamidi & Chavoshi, 2018; Hao et al., 2016; Shyu & Huang, 2011; Tang & Hew, 2017). Many researchers conclude that e-learning gives better results than traditional learning (Paliwoda-Pekoszand & Stal, 2015; Stricker et al., 2011). Virtual Learning Environment (VLE) service is achieved in India through video conferencing tools like Aview, TeamViewer, and Any meeting. The universities connected under the NKN (National Knowledge Network) scheme use this service (Geetha et al., 2017). The e-learning system has been reviewed under two dimensions in this section.

E-learning framework is a conceptual model that measures system quality and learning outcomes. Based on functionality, the framework is subdivided into various dimensions. Each dimension has its attributes to measure e-learning outcomes. The e-learning framework suggested by Sun et al. (2008) is considered as the base for this study. It consists of six dimensions: user/learner, instructor, pedagogy, technology, design, and environmental (Aldhafeeri & Khan, 2016). Even though all dimensions are equally essential to achieve the best outcome, only a few studies are reported on the learner and technological dimension together. Therefore, these two dimensions have been taken for this study.

2.2.1 Technological dimension

It emphasises the technological factors that determine e-learning adoption based on the information system theories (IST). Various system attributes are identified based on these theories. The theories, constructs and items adopted in this study are shown in Table 2.1.

"DeLone and McLean model" (2003) or "Information System Success model" is designed to measure the computer-based system's effectiveness. Based on six constructs, the adoption of e-learning system is analysed. Based on DeLone and McLean model, constructs adopted in this study are system quality, information quality, service quality and collaboration quality.

The system quality provides the hardware and software tools required by the users to complete the course. System quality is measured based on how easily the learners can handle the tools in the online environment. Under this construct, three items are navigation, usability, and flexibility (DeLone & McLean, 2014). Based on these items, the overall performance of the system is determined. Also, system quality directly impacts perceived usefulness and perceived satisfaction (DeLone & McLean, 1992; Kim & Park, 2018).

The quality of the content provided in the online course is also measured under this construct. The online environment's information plays a vital role in registering and continuing the online course. The appropriate content related to the course objective also increases the number of participants. The information provided in the online platform will automatically increase the perceived usefulness and perceived satisfaction of the learners. The previous studies confirm the same result about information quality (Bawack & Kala Kamdjoug, 2020; Lin & Lee, 2006; Lin & Lu, 2000; Machado-Da-Silva et al., 2014). Therefore, the three items adopted under this construct are usefulness, understandability and reliability (DeLone & McLean, 2003; Urbach et al., 2010a, 2010b).

The service quality measures the responsiveness of the system. It promotes timely service and increases user intention towards e-learning (DeLone & McLean, 2003; Mohammed et al., 2017). The past studies concluded that service quality was a critical factor in determining e-learning success (Chang & King, 2005; Uppal et al., 2017). Under this construct, the three items are responsiveness, assurance, and timeliness (Chang & King, 2005).

The communication between instructor and learners and peer-to-peer communication is essential in the online platform. Furthermore, knowledge is shared in the online platform through the collaborative environment (Benbya et al., 2004). Therefore, collaboration quality is added as one of the constructs in this research model. Three items adopted under this construct are effectiveness, comfort and ease of use (Cidral et al., 2018). In this study, two factors, Perceived Usefulness (PU) and user intention to accept technologies or Perceived Satisfaction (PS), is taken from the Technology Acceptance Model (TAM). The learner's belief towards technology and satisfaction is estimated through these factors (Davis et al., 1989; Park, 2009; Sun et al., 2008). PU determines the learner's belief about how technology will improve their performance (Davis, 1998). PU affects e-learning adoption and is considered as an important factor in this study. Four items adopted under this construct are data quality, relevance, tangible and validity (DeLone & McLean, 2014). The IS theories and constructs adopted in this study is shown in Table 2.1.

Table 2.1 Technological dimension: IS Theories and constructs adopted in this study

Author & year	Theories Adopted	Constructs	No of items	Items
Bailey and Pearson (1983); Davis (1998); Gable et al. (2008)	D&M IS Success Model	System quality	3	Navigation, usability, flexibility
Lin and Lee (2006); Lee and Choi (2010)		Information quality	3	Usefulness, understandabilit y, reliability
DeLone and McLean (2003); Mohammed et al. (2017)		Service quality	3	Responsiveness , assurance, timeliness.
DeLone and McLean (2003); Nam and Zellner (2011)		Collaboration quality	3	Effectiveness, comfort, ease of use
Cheng (2012); Brahmasrene and Lee (2012)	Technology Acceptance Model (TAM)	Perceived usefulness	4	Data quality, relevance, tangible, validity.
Sun et al., (2008); Wang and Chiu (2011); Aparicio et al. (2017); Cidral et al. (2018)		Perceived satisfaction	3	Adequate, precision, overall satisfaction
Scott et al., 2008; Kapoor et al., 2014; George, et al., (2014); DeLone & McLean (2003); Urbach et al., (2010)	Diffusion of Innovation Theory	E-learning adoption	3	Relative advantage, compatibility, trialability

Similarly, the learners' Perceived Satisfaction (PS) is measured based on technical ability and awareness. Three items adopted under PS are adequate, precision and overall satisfaction. Previous studies have concluded that the system use and leaner acceptance level could be measured using PU and PS (Al-Fraihat et al., 2019; Cheng, 2012). Hence, PU and PS are added to the conceptual model. Based on the diffusion of innovation theory, e-learning adoption attributes are adopted. According to Zhang et al. (2010), the e-learning adoption factors are learners' perception of relative advantage, compatibility, complexity, observation and trialability. Therefore, in this study, three items: relative advantage, compatibility and trialability are included.

The relative advantage is the learners' belief that e-learning platform is better than a traditional learning environment. Based on convenience, learners prefer to communicate more with peers and instructors in the e-learning environment compared to the traditional learning environment. It would improve the learners' communication skills and motivate them to adopt e-learning platforms (Kapoor et al., 2014; Scott et al., 2008). Compatibility is the learner's belief that a new e-learning platform is compatible with traditional ideas. The quality of the e-learning environment is comparatively better than conventional learning. Trialability is the learner's belief that they are familiar with the e-learning platform before adopting it. According to the experience and satisfaction level of the learner, they would adopt the e-learning platform (Kapoor et al., 2014; Scott et al., 2008; Zhang et al.,2010).

2.2.2 Learner characteristics

Learning theories describe how students obtain and process information from the outside world and enrich their knowledge and skills. Hence, the learners' self-efficacy is considered a core element in the learning theories. Self-efficacy is defined as how people believe themselves to do the task until they achieve the outcome (Sukserm & Takahashi, 2012). The learner's computer self-efficacy and Internet self-efficacy is analysed under learning theories. Based on the social learning theory and social cognitive theory, these two constructs are identified and added as components in the research model (Bagchi, 2005; Hargittai & Shafer, 2006; Hermeking, 2006; Wang & Newlin, 2002).

Computer self-efficacy and Internet self-efficacy are factors that measure learners' technology awareness. Previous studies show that computer self-efficacy and Internet self-efficacy improve online performance. Computer self-efficacy encourages active participation (Chou & Wang, 2000; Simmering et al., 2009). Three items were derived from the social learning theory to measure computer self-efficacy: level of arousal, credibility, and knowledge (Bandura, 1991). Internet self-efficacy increases user participation in the online environment (Joo et al., 2000; Parkes et al., 2015; Thompson et al., 2002). It also improves system utilisation capacity and reduces resource wastage. Three items were derived from the social cognitive theory to measure Internet self-efficacy: performance, collaborative feature, and self-possession (Bandura, 1991). In addition, perceived usefulness and perceived satisfaction were also evaluated based on computer self-efficacy and Internet self-efficacy (Elkaseh et al., 2016; McKinney et al., 2002). The technology awareness about e-learning is measured under the learner dimension. Table 2.2 illustrates the learning theories, constructs and items that measure learners' technology awareness in the current study.

In this study, Bandura's Social cognitive theory has been adopted to choose the other constructs. The learner characteristic is categorised into four divisions: cognitive, behavioural, social and physical attributes. The cognitive factor focuses on what the user knows and how the user interprets information based on previous knowledge. The items under the cognitive factors are the learner's knowledge, attitude and expectation about the online course (Arbaugh, 2002; Jonassen, 1991).

Table 2.2 Learner dimension: Learning theories and constructs adopted in this study

Author and year	Theories Adopted	Constructs	No. of items	Items
Bagchi, 2005; Hermeking, 2006; Hargittai and Shafer 2006; Wang and Newlin, 2002; Tudge and Winterhoff,1993	Social learning theory	Computer self-efficacy	3	Level of arousal, credibility, knowledge
Parkes et al., 2015; Thompson et al., 2002; Joo et al., 2000	Social cognitive theory	Internet self-efficacy	3	Performance, collaborative feature, self-possession

The behavioural factor describes the emotions, thoughts, and attitudes of the learners towards e-learning. It estimates a learner's skills, practice and self-efficacy (Kerr et al., 2006). The social factor describes the collaborative nature of users in an online environment. In a social context, social behaviour, learners' interaction with instructors and peers, and others influence others (de Vreede & Mgaya, 2006; Liaw & Huang, 2010; Moore et al., 2011). Finally, the physical strength of users is measured by health factors. It includes visual ability, auditory ability and other physical conditions of users. This study assumes that learners are physically fit and active in the online platform (Liaw et al., 2007a, 2007b). Therefore, only the first three factors are considered in the study. Based on social cognitive theory, the learner characteristics are included in this study with three items: cognitive (learner attitude), behavioural (learner behaviour) and environmental/social (learner confidence) factors.

Based on cognitive factors from social cognitive theory, the learner attitude is analysed in this study. The previous studies identified learner attitude as one of the critical factors under the learner dimension (Pituch & Lee, 2006). Learner attitude improves the learners' interest in the online platform (Lee & Choi, 2010; Sun et al., 2008). Learner attitude is measured based on the learners' belief to use the online platform. The learners' attitude will motivate them to complete the course successfully (Stern, 1983; Zhao, 2015). Therefore, this construct is adopted with three items: belief, interest and motivation (Piccoli et al., 2001). All the above three constructs are adopted from the social cognitive learning theory. The learner dimension constructs adopted in this study are shown in Table 2.3.

Table 2.3 Learner characteristics: Learning theories and constructs adopted in this study

Author and year	Theories Adopted	Constructs	No of items	Items
Passerini and Granger, 2000; Arbaugh, 2002; Jonassen, 1991; Kerr et al., 2006; Moore et al., 2010; de Vreede and Mgaya, 2006; Liaw and Huang, 2010	Social cognitive theory	learner characteristics	3	behavioural, social, cognitive
Kerr et al., 2006; Venkatesh et al., 2003; Samsudeen and Mohamed 2019; Liu and Feng, 2011; Bo et al., 2014		learner behaviour (behavioural factor)	3	trust, performance expectancy, practice
Moore et al., 2010; de Vreede and Mgaya, 2006; Liaw and Huang, 2010		learner confidence (social factor)	3	internal influence, social collaboration, perceptions
Passerini and Granger, 2000; Arbaugh, 2002; Jonassen, 1991		learner attitude (cognitive factor)	3	belief, interest, motivation
Duffy and Jonassen, 1991; Loh et al., 2016; Agarwal et al.,2000; Jakobsen et al., 2019; Kim et al., 2012; Pritchard and Woollard, 2010	constructivism	learner prior knowledge	3	familiarity, knowledge acquisition, implication

In the current study, Learner behaviour is considered as the behavioural factor from social cognitive theory. Learner behaviour is defined as a trust or belief towards themselves. Many previous studies conclude that the learner's ability to improve self-efficacy will automatically increase learner behaviour (Sukserm & Takahashi, 2012). The performance expectancy would improve learner interest and performance (Venkatesh et al., 2003; Samsudeen & Mohamed, 2019; Liu & Feng, 2011; Bo et al., 2014). It is considered as a part of the online learner characteristics that also reflect in their academics (Bo et al., 2014; Liu & Feng, 2011). Three items adopted under the construct 'Learner behaviour' are trust, performance expectancy and practice.

In the present study, Learner confidence is considered as the social factor from social cognitive theory. Learner confidence is determined based on knowledge and skills (Hung et al., 2010; Saade et al., 2007; Salaberry, 2000; Sukserm & Takahashi, 2012). The internal influence or personal confidence would increase the user's confidence level in the online environment (Park & Wentling, 2007; Qu & Johnson, 2005; Ramaha et al., 2012). Also, the e-learning perception would help to improve the learner's confidence. Previous studies found a significant relationship between learner perception and belief. The discussion in the group and sharing opinions also provides the opportunity to develop the learner's confidence. Thus, social collaboration and communication among peers will increase the confidence level of the learner. Therefore, the items included under Learner confidence are internal influence, social collaboration and perceptions (Diamond & Irwin, 2013).

Finally, prior knowledge is also added as one of the constructs in the research model. Among learning theories, the learners' prior knowledge comes under constructivism theory. This theory's unique feature is that according to this theory the learner can process the information based on previous experience and environmental factors (Duffy & Jonassen, 1991). A constructivist approach improves the performance of the learners based on prior knowledge. It links new information with prior knowledge and interprets it accordingly.

The learners' prior knowledge or experience regarding online courses would improve their confidence (Jacobsen, 2019). Meanwhile, prior knowledge about online courses will also reduce learners' anxiety (Brown, 2010). The previous studies confirm that prior experience is positively correlated with self-efficacy. The familiarity with the computer platform will improve the knowledge level of learners. The prior experience would help them handle online tools and computer resources efficiently (Jeong Kim et al., 2012; Pritchard & Woollard, 2010). Many researchers agreed that the constructivism approach is the best fit for the e-learning environment (Ertmer & Newby, 2013; Hung, 2001). Based on the constructivism theory, the items included in the construct 'prior knowledge' are familiarity, knowledge acquisition and implication.

2.3 Gender-based e-learning adoption in the Indian context

There are many studies conducted to measure e-learning adoption from a different perspective. But there are only a few studies reported for gender-based e-learning adoption. Based on gender, the learning skills of the users differ in the online environment. For example, the study conducted at the University of Granada in Spain concludes that female students are more satisfied with e-learning than male students (Chu, 2010). In addition, the female students are more interested in making online plans and are well-behaved with the teachers in the online platform (Cuadrado-García et al., 2010). However, scholars are less specific in describing gender-based e-learning adoption. For instance, only few studies have been conducted based on gender theories (Huang, 2013; Chan et al., 2009; Aixia & Wang, 2011; Aixia & Wang, 2011; Yawson & Yamoah, 2021; Ouahi et al., 2021).

Even though India has a robust higher education system, there are some limitations to the e-learning system. To enhance the quality of education, online courses like NPTEL are introduced by the Indian Government. The gender-based e-learning adoption towards online courses like Coursera, Edx, Udacity, Khan Academy, Udemy, Alison and NPTEL is analysed in this study. In addition, e-learning adoption is also measured using critical factors like user attitude, satisfaction, technology skills, behaviour, and demographics (Alenezi et al., 2010). The factors like education, gender, and technology acceptance are used to extract how these factors influence individuals' knowledge and e-learning adoption. Therefore, this study concentrates on identifying the influencing factors of e-learning adoption based on gender differences.

2.3.1 Gender-based e-learning adoption: selected country studies

The previous studies related to e-learning adoption from various countries are discussed in this section. Five different countries, including India, are chosen for the literature review. The various e-learning adoptions determinants were selected from other country studies. The details of the chosen country studies are represented in Table 2.4.

Table 2.4: Gender-based e-learning adoption: selected country studies.

Author	Sample size	Methodology	Countries	E-learning adoption determinant
Zaenal et al. (2018)	137 (70 M + 67 F)	quantitative & qualitative	Indonesia	user-attitude
Verma and Dahiya (2016)	904 (560 M + 286 F)	quantitative	India	ICT awareness
Gonzalez-Gomez et al. (2012)	1185 (776 M + 409 F)	quantitative	Spain	user satisfaction
Annette et al. (2017)	22 (15 M + 7 F)	case study	Australia	user behavior
Richard (2011)	719 (302 M + 252 F)	quantitative	United States	user behavior

Note: M denotes "Male", and F denotes "Female."

In Indonesia, gender differences in technology use among school students were studied. Both qualitative and quantitative methods were used to perform the analysis. This study confirmed a gender difference in e-learning adoption in Indonesia (Ursini & Sanchez, 2008; Vale & Leder, 2004; Leyva, 2017). However, only the gender difference in technology awareness was analysed in the study. The study concentrated only on a technological perspective, and user attitude towards technology was recommended for future research. Therefore, the user attitude is considered as one of the constructs in the study (Abidin et al., 2018).

Verma and Dahiya (2016) conducted a gender-based ICT awareness survey among students in Indian universities. 904 samples were collected from Indian universities. As a result of this study, the authors concluded that there is no gender difference in e-learning ICT awareness. The construct ‘technology awareness’ of the current study is included to validate the results and check the awareness level in south Indian universities.

The study conducted in Spain universities concluded that female students are more satisfied than male students (González-Gómez et al., 2012). But some studies gave different results. Lu and Chiou (2010) stated that male students are more satisfied than female students in e-learning adoption. On the contrary, some studies concluded that there is no significant difference between males and females in e-learning adoption (Cuadrado-García et al., 2010). The contrasting results from previous studies show that the satisfaction level varies among users. Therefore, perceived satisfaction is included in this study to analyse the satisfaction level of Indian students.

At the University of Newcastle in Australia, a case study was conducted to analyse the online behaviour of male and female students. The case study concluded that student individuality plays a vital role in the e-learning environment. The result shows that female students are more active in the online environment compared to male students. In addition, the lack of communication is identified as an essential barrier during e-learning adoption (Forgasz et al., 2014; Anderson & Haddad, 2019). Similarly, In the USA, the social presence of male and female students in universities was analysed. The result showed that female students communicate among peers in the online environment (Barrett & Lally, 1999). This study also identified that there are only limited studies on users’ communication and collaborative nature. Social presence and interaction are considered as essential factors in e-learning adoption. Therefore, the user behaviour construct is included in the study.

2.3.2 Learning theories in e-learning adoption

In this study, two different theories are used to measure gender-based e-learning adoption. First, feminist theory is explored to identify gender inequality on various attributes. Second, constructivism is used to measure the individual and social activities of the user in the e-learning platform.

Feminist theory:

Gender inequality comes under feminism/feminist theories as suggested by Lorber (2010) and feminist theory was utilized to identify gender inequality on various attributes in the current study. Previous studies have considered gender differences in technology adoption similar to the present study. The findings of the previous studies revealed that women are more improved in educational attainment compared to men. Heffler (2001) stated that female students' performance is high and more active in the learning platform. The female students preferred more hands-on learning and are people-oriented, whereas the male students are adapted to the analytic approach. Therefore, it creates a gender gap in e-learning adoption. Moreover, past studies also considered gender differences in technology adoption (Minton and Schneider, 1980; Weiner et al., 2003; Maldonado et al., 2010). Therefore, gender is included as a key moderator in this study. Learning theory is mapped with the e-learning relevance and shown in Table 2.5

Table 2.5: Mapping learning theories with e-learning adoption attributes based on gender difference

Authors	Theories	Description	E-learning adoption attributes based on learning theories
Brabeck et al.(1997); June (1994); Limerick and Jane (2006); Regine and Schmidt (2012)	Feminist theory (gender difference theory)	It explores the gender inequality in various domain	Gender
Nahl (1998); Bystrom (2000)	Cognitive constructivism (learning theory)	It describes how an individual build their mental model based on learning skills through experiences	Individual performance
Vygotsky (1978); Savery and Duffy (1995); Gruender (1996); Palincsar (1998)	Social constructivism (learning theory)	It describes the active participation and interaction of the users in the online platform	Social behaviour

Constructivism

Cognitive constructivism is developed based on Piaget's theory, which determines how individuals can build their mental model based on their learning skill through experience. In the late 1990s, due to the user-orientation revolution in information systems, the passive learning process is converted into an active form (Nahl, 1998). Therefore, cognitive constructivism measures the way individuals react to their emotions and cognitive states. The individual performance of the user towards e-learning adoption is measured under cognitive constructivism (Bystrom, 2000).

Social constructivism is defined as knowledge gained through the active participation of the learners in the e-learning platform. The interaction between peers and the collaborative environment is considered as a critical factor in online courses (Vygotsky, 1978; Savery & Duffy, 1995; Gruender, 1996). Thus, the social constructivist approach encourages traditional classroom culture in the virtual platform. Individual behaviour and knowledge are reflected in the coordination activity of the user. It also determines how the users themselves relate to the learning environment. The socio-cultural factors play a vital role in social constructivism (Palincsar, 1998). Therefore, this approach is used to analyse how user behaviour influences e-learning adoption.

2.3.3 *Mapping e-learning dimension with learning theories*

The previous studies analysed direct and indirect e-learning adoption factors through the technology acceptance model (TAM) (Sanchez et al., 2013; Tarhini et al., 2013). However, this study analyses direct e-learning adoption factors through a constructivist approach. In this study, two dimensions of the e-learning framework, namely the learner dimension and technology dimension, are analysed. The four factors that influence e-learning adoption are user attitude, technology awareness, perceived satisfaction and user behaviour. Many students dropped out of online courses due to cognitive and social learning differences (Annansingh & Bright, 2009; Horton, 2000). Therefore, these four attributes are included in this study. Based on these attributes, the e-learning adoption in the Indian context is analysed. The list of gender-based e-learning attributes identified in the study is shown in Table 2.6.

Rogers (1995) strongly believed that e-learning adoption depends on individual performance. As shown in Table 2.6, there are three factors, namely user attitude, technology awareness, and perceived satisfaction, which measure the user's individual performance based on gender (Wild et al., 2002; Hsbollah & Idris, 2009).

Attitude is defined as a user's supportive mindset towards e-learning courses. The main purpose of analysing the user attitude is to measure the acceptance level of e-learning services. The factors that influence attitude are user goals, beliefs, needs and quality of e-learning courses (Aixia & Wang, 2011). The previous studies identify user needs, attitudes towards technology adoption and internet usage as influencing factors under perceived characteristics (Hsbollah & Idris, 2009).

Table 2.6: Gender-based e-learning adoption attributes identified in the study

<table>
<tr><th>Authors</th><th>E-Learning dimension</th><th>Learning theories</th><th>E-learning adoption attributes</th><th>Sub-factors</th><th>Remarks</th></tr>
<tr><td rowspan="3">Sun et al. (2008);
Piccoli et al. (2001);
Arbaugh (2000);
Arbaugh (2002)
Arbaugh and Duray (2002.

Bishop 2006;
Jaiyeoba and Iloanya,
2019; Folorunso et al
2006; Mick and Fournier 1998
Shea et al.,2005
Liaw 2008;
Liawa and Huang 2013; Chan et., al 2009;
Wang, 2003;
Aixia and Wang,2011;
Smith et al.,2000</td><td>Learner dimension</td><td rowspan="3">Individual performance (Cognitive constructivism)</td><td>User attitude</td><td>belief, needs, and attitude towards technology adoption and Internet usage</td><td>users' perception of e-learning adoption</td></tr>
<tr><td>Technology dimension</td><td>Technology awareness</td><td>familiarity with e-learning technologies, computer skills, familiarity with e-learning technologies, prior knowledge about the online course, and Internet usage</td><td>user awareness towards ICTs skills and Internet usage</td></tr>
<tr><td>Learner dimension</td><td>Perceived satisfaction</td><td>perceived usefulness, perceived use, perceived self-efficiency</td><td>perceived satisfaction of users based on the e-learning system quality and instructional quality</td></tr>
<tr><td>David et al., 2007; Sukanlaya et al., 2013; Pedersen 2005</td><td>Learner dimension</td><td>Social behaviour (Social constructivism)</td><td>User behaviour</td><td>Communicative and collaborative nature of the users</td><td>User behaviour in the online platform</td></tr>
</table>

According to gender differences, user's likes, dislikes and intention to use e-learning services vary. Bielaczyc (2006) identified that the user's belief to use the e-learning system is critical. The recent studies concluded that the user attitude and behaviour influence factors in adopting e-learning (Jaiyeoba & Iloanya, 2019). Folorunso et al. (2006) found that technology awareness is critical for e-learning adoption. User awareness towards ICTs and the Internet are considered as influencing factors in technology awareness. The technical skills, including the usage of ICTs and the Internet, are analysed through various factors. The lack of awareness regarding e-learning tools and improper utilisation of the Internet automatically leads to the failure of e-learning services. Therefore, prior knowledge about the online course helps to understand the system in a better way. The user with computer skills and previous experience handles the online environment efficiently.

Perceived satisfaction is defined as the degree of user comfort and user acceptance to e-learning adoption. This perceived satisfaction increases the positive attitude and willingness of users towards e-learning (Shee & Wang, 2008; Lindgaard & Dudek, 2003; Kim & Omg, 2005; Liu et al., 2009). The perceived satisfaction measures individual performance based on perceived usefulness, perceived ease of use and perceived satisfaction (Sun et al., 2008; Piccoli et al., 2001; Shea et al., 2005). The degree of user belief to improve learner performance is measured using perceived usefulness. The usability of the e-learning system is measured under the perceived ease of use (Lee et al., 2009; Tsai, 2009). Finally, the perceived self-efficiency measures the user confidence level and belief towards e-learning (Bandura et al., 1999).

In addition, as shown in Table 2.7, this study identifies “user behaviour” as an important attribute in gender-based e-learning adoption. Previous studies concluded that social constructivism enables an effective e-learning environment through the active participation of users. It also facilitates a better platform to share ideas and interact with other participants in the learning environment (Brown et al., 1989; Lave & Wenger, 1991; Vygotsky, 1978). Based on social learning theory, the intrinsic motivation of the user is estimated. This motivation improves the self-efficacy of the users in the e-learning environment. How the users communicate and coordinate with the online course will increase the confidence level of the users. It also reflects in their achievement and academic activities. The users’ willingness to rise in online courses increases the user intention to adopt the e-learning system (David et al., 2007; Samsudeen, 2019). Thus, the communicative and collaborative nature of users is considered under the user behaviour attribute in the current study on gender-based e-learning adoption.

2.4 E-learning barriers faced by Indian Universities

The growth of ICTs provides new tools and services for e-learning, which enrich the digital environment (Shirazi et al., 2010). Although an online platform provides many advantages, there are many challenges while implementing teaching-learning activities (Cruz et al., 2017). The instructor-participant gaps and technical skills are considered as important research areas in recent years (Joung & Son, 2014; Kassab et al., 2015;

Nikolopoulou & Gialamas, 2016; Islam et al., 2011). However, the challenges faced during implementing e-learning have been inadequately discussed (Abhiyendra, 2007; Deursen et al., 2017; Gunkel, 2003; Mariscal & Judith, 2005; Zhong, 2011; Shafei, Salem & Otoom, 2015; Parayitam, Desai & Eason, 2010; Murphy, 2021; Pérez-Amaral et al., 2021).

The parameters that determine the effectiveness of e-learning are more connected with technologies. Moreover, e-learning is considered a socio-technical system which interlinks technology with users and instructors. A creative and collaborative environment occurs between users and instructors as well as among peers (Upadhyaya & Mallik, 2013). The e-learning system has been developed in the online environment with technological support, enabling the instructor to share knowledge with users.

This study aims to investigate the e-learning barriers in the Indian context. These issues are discussed from different angles as follows: i) technological perspectives and learner perspectives, and ii) organisational perspectives and social perspectives.

2.4.1 E-learning barriers in technological and learner perspectives

From the learners' perspective, motivation and user skills must be transferred into user behaviour to achieve a better e-learning outcome. According to Baldwin and Kevin (1998), user characteristics are critical in transferring user motivation to behaviour. Moreover, the e-learning system is user-centric. Without a balanced focus on user and instructor, it is not possible to achieve the learning objective. Even though same Learning Management System (LMS) is used, the users do not have the same perception, prior knowledge and satisfaction level towards e-learning. Therefore, the digital divide in e-learning is based on integrating users' requirements with technological factors (Lim et al., 2013; Kilic, 2010).

From the technology perspective, an e-learning environment enables users to interact with forums, instructors, and peers through e-learning tools. The technological factor determines the cognitive level of learning, appropriate pedagogy, and collaborative approach in the learning environment (Victor et al., 2016). Alavi and Leidner (2001) argued that the equity of e-learning is achieved when technology and pedagogy are integrated. Technology-mediated learning and virtual learning framework are used to fulfil the teaching and learning process in a digital environment.

Even though India is considered an appropriate place for the progress of e-learning, there is no proper technology access in rural areas. However, Internet penetration is more in urban areas, and thus awareness of technology usage is more compared to rural areas (Govindasamy, 2002; Hasan et al., 2007; James, 2009). The unequal distribution of digital resources and services creates a digital divide in developing countries like India. It also increases the individual e-learning gap among users from rural areas (Petya et al., 2018

According to OECD (2000), the standard definition for "digital divide" is a gap between individuals, households, businesses and geographic areas at different socioeconomic levels regarding their opportunities (Frederico et al. 2012; Julian et al., 2008; Srinuan et al., 2012). The global digital divide describes the unequal distribution of computer resources and Internet technology (Monica, 2018; Frederico et al., 2012; Wijers, 2010, Jyoti et al., 2018). The digital divide is classified into four dimensions. The first dimension identifies the economic and social inequality to access infrastructure and Internet facilities. The second dimension of the digital divide explores the individual and social use of ICTs and Internet resources. The third dimension is concerned about the efficient use of resources by individuals and across geographical differences (Ben Youssef, 2004). Fourth, the learning related to the knowledge-based economy. Even though the digital divide has four dimensions, only two dimensions are considered for this study. The two digital divide dimensions, namely technological barriers and individual barriers, will be analysed using quantitative method (survey method). Thus, the major focus of this study is to find a solution for the digital divide and reduce the technological and individual barriers.

In this context, the 'individual barriers' is the main hazard to implementing e-learning in an effective way (Wolfgang et al., 2016; Joo et al., 2003). The e-learning barrier consists of three dimensions, namely individual, technical and organizational barriers. The contextual barrier framework has been taken as a base for this study (Pikkalainen and Pawlowski 2014). The current study focuses on two dimensions: individual barriers and technical barriers (Stoffregen et al., 2015). In addition, the digital divide is considered as an essential factor to overcome the e-learning barriers in the learning environment. Hence, this study focuses on technological and individual barriers in the digital divide perspective.

2.4.1.1 Technological barrier

The growth of ICTs and broadband networks has more advantages in the digital environment compared with the traditional learning environment. The proper usage of technology in the learning process helps achieve desired learning outcomes and positively influences e-learning adoption (Alavi & Leidner, 2001; Lee et al., 2015**)**. In addition, the technology enables to access facilities and integrate the users to make a collaborative online environment. Unfortunately, inequality in technology usage and lack of Internet facilities create a digital divide problem in developing countries like India.

The technological barriers include lack of online resources and Internet connectivity, insufficient bandwidth and system interface related to the learning environment. The technological barriers occur in geographically remote and technologically alienated areas due to social and economic deprivation (OECD 2000). Due to geographical differences, the social and technical challenges are considered critical factors in the digital divide (Deursen et al., 2010).

Based on access to ICTs and Internet facilities, the digital divide is classified into two types as international and intra-national. This study focuses on the intra-national digital gap in the Indian context. Besides location, the lack of users' experience related to new technology is also discussed in this study. Hsieh et al. (2008) argued that the financial status of the users plays a major role in using ICTs confidently because economically advanced users have more exposure and they easily adapt to new technologies.

The rural areas in India are affected by the digital divide problem due to the unequal distribution of hardware, software, and other network issues (Abhiyendra, 2007; Hasan et al., 2007). Even Internet connectivity, Internet quality, and Internet speed are considered critical factors in developing countries. However, in Mexico, the situation is entirely different, where the vast deployment of telecommunication networks does not narrow the digital gap (Luis et al., 2007; Julian et al., 2008). This is due to the unequal distribution of IT resources in that country. The result of this study clearly shows that the development of telecommunication facilities without proper ICTs deployment cannot reduce the digital gap (Mariscal & Judith, 2005; Puspitasari & Ishii, 2016). A summary of the digital divide dimensions and factors are shown in Table 2.7.

Table 2.7 E-learning barrier factors identified through this study

Author	Barrier dimension	Factors	Remarks
Abhiyendra (2007); Deursen et al. (2017); Gunkel (2003); Mariscal and Judith (2005); Zhong (2011); Bagchi (2005); Hermeking (2006); Hargittai (2001).	Technological barrier	Lack of ICTs facilities Lack of Internet Discomfort in ICTs use	The system factors that influence barriers affecting e-learning adoption.
Dijk (2003); Lee et al. (2014); Pearce and Rice, (2013); Van et al. (2017); Kassab, Shafei, Salem and Otoom (2015); Parayitam, Desai and Eason (2010); Eunjin et al. (2009).	Personal/Individual barrier	User anxiety Lack of digital literacy Lack of prior knowledge	The learner factors that influence barriers affecting e-learning adoption.

The ICTs deployment includes infrastructure service, network facilities, economic factors, and other government implementation policies. The low penetration rate of ICTs creates the digital divide issues in e-learning. On the other hand, the growth of ICTs improves the digital environment and encourages people to use those benefits (Mohammad et al., 2009; Zhong 2011). The quality of learning outcomes depends upon technologies used in the online platform (Hermeking 2006). Hence, the digital divide is considered as a strategic tool to reduce limitations in the e-learning system. In developing countries, learners' age and urban population are connected with ICTs, but Internet cost is not significantly correlated (Li and Ranieri 2013; Cruz-Jesus et al., 2016). But many past studies confirm that Internet facility is significantly correlated with the e-learning system (Grazzi et al., 2012; Pagán et al., 2018). Thus, the unequal distribution of the Internet increase costs and reduce the downloading speed of online courses. Therefore, the lack of Internet connections in rural areas is one of the main reasons to create a new divide. Access to ICTs through poor Internet quality and low speed decreases user interest in the online platform. A proper combination of the Internet with online resources will increase the efficiency of e-learning. Thus, the Internet is used as a medium to establish communication between user and instructor.

Many universities used broadband connection or Intranet as a base for collaborative online learning. Apart from the Internet, telecommunication networks, personal computers, and cell phones are also used as a medium in e-learning (Bagchi 2005; Luis et al., 2007; James 2009; Lee et al., 2015). The digital divide is a gap between individuals and organisations in different geographical locations to access computer resources and the Internet (Frederico et al. 2016, Petya et al. 2018).

2.4.1.2 Individual barrier

The individual barrier outlines the lack of cognitive and behavioural skills of the user. To reduce personal barriers, it is essential to empower users in an online environment with appropriate training. It helps to bridge the individual barrier and reduce the digital divide in the teaching-learning process (OCED 2000). Many researchers state that computer literacy, Internet skills, social status, gender, unequal financial status, and culture lead to digital divide issues, other than technological facts (Dijk 2003; Alexander & Jan 2010). The lack of leaner' motivation, attitude and Internet usage to access digital content also creates a digital divide. However, social inequality is considered one factor for the unequal distribution of online resources (Lee et al., 2014; Pearce & Rice 2013; Van et al. 2015).

The e-learning gap outlines the lack of cognitive and behavioural skills of the user. Empowering users in the online environment with appropriate training helps to bridge the e-learning gap and reduce the digital divide in the teaching-learning process (OCED 2000). It also improves the efficiency and effectiveness of an e-learning system. Apart from technological factors, computer literacy, Internet skills, social status, gender and unequal financial status also lead to digital divide issues (Dijk 2003; Alexander & Jan 2010). Similarly, the lack of learner motivation, attitude and Internet facility to access digital content also creates a digital divide gap. However, social inequality is considered as the main reason for the unequal distribution of online resources (Lee et al., 2014; Pearce & Rice 2013; Van et al. 2015).

From a user's perspective, time and connectivity issues are considered as critical factors arising from zonal time differences in synchronous learning modes. Thus, it increases personal barriers between users and the instructor and reduces interaction time within the digital environment. Therefore, the time scheduling issue is an essential factor in the synchronous way of teaching (Bostrom, 2012). In addition, the lack of user willingness and motivation towards e-learning increase the digital divide (Kassab et al., 2015). Even though the e-learning system is the same, users' perception, prior knowledge, and satisfaction level may not be the same (Lim et al., 2013; Picciano, 2002).

Inadequate instructors with a lack of ability to connect technologies with learning needs are critical challenges in the online environment. Moreover, in many developing countries, users face problems in accessing materials and communicating with instructors. The users have less exploration and awareness about online resources due to locality differences. Though technology development provides many benefits over the traditional learning process, it also has negative side effects. It causes tension, computer anxiety, stress to users and reduces the real-world communication between users (Parayitam et al., 2010).

A learner's performance is measured based on how the user understands and handles the online resources in the learning environment. A learner with a negative attitude and computer anxiety does not perform well and does not complete the task assigned in an online course. It reduces their interest to register for future online courses and decreases their satisfaction (Chou, 2001). According to Frankola (2001), the main reason to drop out of online courses in the middle is the lack of motivation and not technology issues. The insufficient skill of the user causes failure in online activities and increases the digital divide. Other reasons considered under learners perspective are learning style mismatch, time conflicts, family situations, and university support (Upadhyaya & Mallik 2013).

Learners' financial status to access a digital resource is also counted as a limitation (Deursen et al., 2017; Gunkel, 2003).

On the other hand, the learners' Internet self-efficiency and computer literacy help utilise the full benefits of e-learning. Computer literacy includes retrieving online material, proper use of online resources, and communication with instructors and/or peers in the online environment, which will improve the learner's performance and enhance e-learning adoption (Hargittai & Shafer, 2006).

2.4.2 E-learning barriers in organisational and social perspectives

E-learning facilitates interaction between the students and the experts through a digital system. The virtual classroom setup is enabled to deliver the learning content through the Internet as a medium. Compared to traditional learning, e-learning provides easy accessibility in developing countries (Acharya and Lee 2018; Wang et al., 2009). The Global Competitiveness Index report (2018) states that the quality of institutions in India has increased in terms of public spending; However, private sectors suffer from barriers and problematic factors such as corruption, infrastructure, lack of educated workforce, innovation and policies. Therefore, it clearly specifies that inadequate infrastructure facilities, lack of an educated workforce, and policy instability are considered critical barriers in India.

The e-learning barriers are classified into 68 factors. In Technology, Individual, Pedagogical, and Enabling Conditions (TIPEC) framework proposed by Ali et al. (2018), these factors are grouped into four categories: technological, individual, pedagogical and enabling conditions. In addition, the e-learning barrier framework has various dimensions to identify the e-learning challenges. As per the Contextualized Barrier Framework, e-learning barrier dimensions are classified into three categories: contextual, social and technological dimensions (Stoffregen et al.,2015; Deggs 2011). Even though many barriers and dimensions are identified in the past literature, this study focuses on the technological barriers. Especially, the seven technological challenges, namely infrastructure, Internet, software interface design, compatible techniques, system quality, and system security, are analyzed in this study (Gutiérrez-Santiuste et al., 2016; Golbeck et al., 2010; Marzilli et al., 2014). The technological challenges identified through this study are listed in Table 2.8.

Table 2.8: Technological challenges identified through this study

Authors	E-learning barrier dimension	Technological challenges	Remarks
Gullu et al.,2016; Alsabawy et al., 2013 Shelton 2011	Organizational Perspective	Infrastructure	It refers to the hardware, software and other network utilities used in e-learning.
Gutiérrez-Santiuste et al., 2016; Mahanta & Ahmed 2012, Poon et al.,2010		Internet	It indicates Internet connectivity, speed, and bandwidth during e-learning
Nai & Madhav 2017; Marzilli et al., 2014		System quality and software interface design	The quality of system and interface used in the e-learning environment
Acharya & Lee 2018; Van et al., 2017; Zhong 2011; Sun et al., 2018	Social Perspective	Digital divide	Unbalance technology distribution due to geographical boundaries

According to Stoffregen et al., 2015, the technological barrier challenges are also broadly classified into two perspectives, namely organization and social barriers. The organization barrier includes infrastructure (software/hardware, network utilities), Internet, and system quality/software interface. The unbalanced distribution and lack of access to digital resources lead to social barriers. Thus, the inadequate and unequal distribution of online resources is considered as a technological barrier in the e-learning system

2.4.2.1 Organizational Perspective

Most of the universities in developing countries have inadequate e-learning infrastructure facilities. There is no proper financial support provided by external sources due to policy instability. Therefore, the higher education institutions (HEI) suffered from inadequate infrastructure facilities such as software, hardware and other network utilities. In some cases, though sufficient digital resources are available, it is wasted due to lack of technological awareness. This creates technological challenges in the e-learning system. Secondly, the lack of Internet quality, connectivity, and speed are considered to be critical factors. Without proper Internet support, it is impossible to provide an efficient e-learning system. It automatically reduces the quality of an e-learning system (Nai & Madhav 2017; Stoffregen et al., 2015)

2.4.2.2. Social Perspective

The digital divide or digital gap is a social issue in which digital resources are not equally distributed among society. According to OECD (2001), the standard definition of the digital divide is "the gap between individuals, households, business and geographic areas at different socioeconomic levels with regard to their opportunities to access the ICTs and Internet for a wide variety of activities”(Cruz-Jesus et al., 2012; Sims et al., 2008). It creates a digital gap between people who can gain the ICTs benefits and those who cannot. This leads to lack of access to ICTs by particular communities (Scrutiny of Acts and Regulations Committee, 2005; Hilbert 2014).

2.5 E-learning platforms

Two different e-learning platforms, namely cloud platform and mobile platform that promote e-learning services, are reviewed under management dimension. First, the adoption of mobile apps in special education is reviewed based on different types of disabilities, ATDs and factors that influence special education. Second, the user awareness towards mobile apps, including civic and e-learning services, are discussed from the end-user perspective. Third, different e-learning challenges, including organizational and social factors, are reviewed. In addition, cloud benefits depending on Quality of Service (QoS) parameters like availability, scalability, reliability and performance are identified through selected country studies. Based on the above factors, the literature is discussed.

2.5.1 E-learning in special schools

The World Health Organization states that “disability is not just a health issue; it also includes the interaction between the features of a person’s body and the features of the society he/she lives in”. The disabilities include impairments such as body function and structure, activity limitation which is an issue that an individual faces when doing a task, and participation restrictions which indicate a lack of participation in day-to-day activities (Chuan et al., 2018). Blindness, intellectual disability, partially or completely missing limbs, autism, cancer, cerebral palsy, human immunodeficiency virus (HIV) infection, multiple sclerosis, muscular dystrophy, major depressive disorder, bipolar disorder, post-traumatic stress disorder, obsessive-compulsive disorder, and schizophrenia are among the disabilities listed in the Americans with Disabilities Act of 1990 (Federal Register 2011). According to Hutchison, the dimensions of disabilities (1998) are “locomotion, fine motor, personal care, Constance, hearing, vision, communication, continence, learning, behaviour and social integration, physical health and consciousness.”

Special Education (SE) refers to an educational service provided by the public and private educational institution to differently-abled individuals between the ages of 3 to 21 years. According to the individual needs, SE include planning, systematic monitoring, adapting technical support and accessibility service (Evgenii et al., 2018). The modern education system responds to the needs of special students with assistive technology devices and mobile learning technologies (Mechling, 2007; Alghabban et al., 2017). Many types of research have been conducted to analyse the use of assistive technology to enhance learning with a group of disabled students. However, only a few types of research have been done with the global standard. According to Liu, Wu, and Chen (2013), the most common technologies used in special education are laptops, computer-based learning games and web-based learning. In the current study, the author addresses the effectiveness of m-learning apps in special education.

In developing countries like India, separate policies and schemes are introduced for the improvement of special children. According to the Education Law for the disabled, Article 29 (2) provides that “no disabled citizen shall be denied admission based on religion, caste, race or language”. Similarly, Article 45 implements that the state should provide compulsory and free education for all children, including the disabled, until 14 years. According to the United Nations Children’s Fund (UNICEF) report 2017, it has introduced development plans across India since 1949. The Anganwadi workers in 18,000 centres support primary school students in India. In addition, the State Council of Educational Research and Training as well as the District Institute of Education and Training focus on the teaching-learning process with specific technical support. It has also strengthened child-friendly pedagogy, integration of ICTs and teacher educator capacities in India.

Along with the Government policies, Assistive Technology Device (ATD) was introduced in the modern education system in special education. Assistive technology helps to bridge the learning environment with disabled students. According to section 300.5 in the Individuals with Disabilities Education Act (IDEA) 1990, “the assistive technology device is a piece of equipment that is modified and used to improve functional capabilities of a child with a disability” (Mechling, 2007). According to the individual needs, ATD is modified to overcome the difficulties faced by disabled students (Encarnaco et al., 2016).

Existing articles often describe the importance of ADTs in special education. Even though the ATD has improved special education in many ways, it remains unreachable for a large number of disabled students. Developing countries like India have limitations, such as availability and affordability (Ismaili, 2017). Therefore, mobile learning (m-learning) is introduced as an alternative solution to overcome the limitations (Godwin, 2011). However, only less research has been conducted on m-learning platforms for special education, in general, and to explain its use among special education in specific to the Indian context (Stevens et al., 2013; Wilson et al., 2017; Jiam et al., 2016; Chuan et al., 2018; Abuzaid, 2021; Al Rawashdeh et al., 2021).In this study, m-learning using smartphones and tablets is considered as an alternative learning tool against ATD. The various m-learning applications are compared with the ATD at the level of availability, affordability and other factors. The comparison is made relevant in the case of physical and mental disabilities as well.

In the past decades, special groups face communication problems within the school and society. Though majority of the mobile application developers do not consider these special groups, many organisations concentrate on special need students (Anuar et al., 2014). As a result, many mobile gadgets with open-source apps are introduced as alternative monofunctional ADTs in the formal and informational learning platforms. According to Hulme and Shield (2008), mobile is treated as a mediating device promoting e-learning anywhere and anytime. This unique feature enables the growth of m-learning in special education. For instance, the research team of the University of Granada and the University of Murcia deployed a mobile platform in iPad and iPod devices. It promoted m-learning for special need students (Fernandez et al., 2013).

Similarly, the Google play store consists of many mobile apps for special students. Ismaili (2017) concluded that mobile apps had fulfilled the needs and satisfied students with special needs. These mobile apps ensure availability and provide affordable service to disabled students. Meanwhile, the increasing number of open-source mobile apps also confuses students in choosing the correct application. Therefore, this paper identifies and suggests different types of mobile apps for disabled students.

2.5.1.1 Different types of disabilities included in the study

The growth of ICTs supports special students with various disabilities. The technology must be integrated according to special students' needs, strengths, and interests (Aresti et al., 2014). The technological tools used in special education are called "Assistive Technology" (AT). It plays a vital role in special education classrooms. According to the Individual Disabilities Education Act 1990 (IDEA), the AT concept is subdivided into three sections: what is AT, how it is made and how it is used. The first part defines AT itself, whether it is an electronic device or system component. The second explains whether AT is purchased or modified according to the specific need. The third relates to using AT for special needs (Bryant & Bryant 2003; Individual with Disabilities Act, 2014). According to the Elementary and Secondary Education Act 1967, ATD was made compulsory in special education. Later this Act is renamed as IDEA, which provides a guideline to use ATD for disabled students.

On the other hand, educators state that it is challenging to adopt the technology as per the need for disabled students. In addition, the insufficient ICT skill and awareness of the teachers/students, attitude towards particular technologies, the cost of new technologies, lack of resources, lack of maintenance and technology supports are other challenges faced in special education (Okolo et al., 2014; Lee & Vega, 2005; Brodin & Lindstrand, 2003).

As per the IDEA report, disabilities are classified into two categories. The "high incidence" category includes learning disabilities, intellectual disability, and emotional disturbances. The "low incidence" category includes autism spectrum disorders, traumatic brain injury, language and speech disorders (communication), hearing disorders and deafness, vision disorders and blindness, severe and multiple disorders, other health impairments, and physical disabilities. In this study, special students with six different disabilities are taken into account as shown in Table 2.9

Table 2.9: Different types of disabilities included in the study

Author(s)/Year	Disability categories	Remarks
Bartolome et al., (2014); Suzanne et al., (2019); Aura et al., (2014); Pascoloni and Mariotti (2012)	Blindness/low vision	Inability to see or to discern the light
Chuan et al. (2018); Wilson et al. (2017); Jim et al. (2016); Stevens et al. (2013)	Hearing impairment	Partial or complete loss of hearing ability
Ghaleb (2019); Rodenbanum et al. (2010); Olaleye et al. (2012)	Intellectual disabilities	It is affecting the functioning of two areas: intellectual and adaptive functioning.
Priscilla et al. (2019); Douglas et al. (2019); Dennison et al. (2014); Cornell and Allen (2011); Cornell (2011)	Mental illness	Change in emotion, behaviour and thinking
Qianqian et al. (2018); Kathryn et al. (2017); Sezer et al. (2015); Liu et al. (2013)	Locomotor	Physical and mobility impairment
Jill et al. (2018); Margaret et al. (2018); Bennett et al. (2014); Levy et al. (2011)	Autism spectrum	It affects behaviour and communication

.

Blindness is defined as the inability to see or discern light from darkness (National Federation of the blind). India is now home to one-third of the world's blind population (Tribuneindia News Service, 2021). According to the World Health Organization (WHO) report 2018, 12 million people out of 39 million total blind population are in India (Aura et al., 2014; Pascoloni & Mariotti, 2012). Visual impairment also reduces the social activity of the special student (Suzanne et al., 2019). The quality of life and behaviour adoption are also affected by vision impairment (Bathel et al., 2019).

The complete or partial loss of hearing ability of one or both ears is called hearing impairment. The highest significant hearing threshold is 81 dB, and the average frequencies are 0.5, 1, 2, 4 kHz. World Health Organization report (WHO) 2021 states that the half deaf and hearing impaired are unavoidable, and one-third of these people live in developing countries like India (who. int, 2021). Special education schools are responsible for the social and behavioural improvement of special students (Stevens et al., 2013; Wilson et al., 2017; Jiam et al., 2016; Chuan et al., 2018).

According to the World Health Organisation, intellectual property generally affects two functional areas: intellectual functioning and adaptive functioning. Ghaleb (2019) suggested that the coordinating system will improve the social and behavioural factors of intellectually disabled students. For example, the special school in Riyadh geographically distributed its branch within the city, but implements the same special education program scheme in all branches. It also arranges combined classes with other branches. Thus, the integration of schools improves the interaction of the special students (Rodenbanum et al., 2010; Olaleye et al., 2012; Kathryn et al., 2017; Liu et al., 2013; Sezer et al., 2015; Qianqian et al., 2018).

According to the American Psychiatric Association, mental illness is defined as "a health issue involving changes in emotion, thinking, and behaviour". It is associated with distress functioning in work, family or social activities (Cornell, 2011). In the special education institution, the psychologist and counsellors play an essential role in evaluating special students. These members are responsible for giving the input for the Individualised Education Program (IEP) team (Cornell & Allen, 2011; Dennision et al., 2014; Douglas et al., 2019; Priscilla et al., 2019).

The physical and mobility impairment includes various types of disabilities such as loss or abnormalities of the upper and/or lower limb. This problem occurs due to the consequence of diseases or ageing. In addition, the individual who has a broken skeletal structure is also included in this disability category. Spinal cord injury is the main reason for this disability. The assistive devices and mobility aids are used in their learning environment (Kathryn et al., 2017).

Autism is defined as one of developmental disorder that influences the individual's behaviour and communication. The Autism Spectrum Disorder (ASD) people have difficulties interacting with others and are unable to function correctly in schools and workplaces (Bennett et al.,2014; Levy et al., 2011; Margaret et al., 2018; Jill et al., 2018).

2.5.1.2 Assistive Technologies in special schools

Dell et al. (2008) and Abel (2018) categorises the AT tools used in special education from low technology to high technology. For low technology devices, the availability and affordability factor of the standard technology tools is high compared to other categories. This device includes no electrical or electronic component, electricity and power resource to operate the devices (York and Fabrikant 2011). Under low technology ATD, flashcards, communication boards with picture and pencil grips are categories. The digital device with less complexity and less training to operate are classified under mid technology devices. It includes calculators, audiobooks, electronic dictionaries, and digital recorders. Finally, the high technology ATD has advanced functionality based on computer technologies. For example, tablet devices and iPads are considered as high technology ATD (Emma et al., 2016). The different types of ATD tools are listed in Table 2.10.

Table 2.10: Various types of Assistive Technology Devices (ATDs) identified in this study.

Authors/ year	ATD categories	ATD name	Remarks
Dell et al. (2008)	Traditional ATD (Low and Mid technology ATD)	Pencil grips, Reading guide Flashcards, Raised line paper, grid paper	The most common form of assistive device available in special classrooms
Kagohara et al. (2012)		Digital recorder, Portable note-taker, Audiobook, MP3 player	Only limited special schools used this assistive technology.
Melhuish and Falloon (2010); Johnson (2013); McNaughton (2013); Watts (2012); Franklin (2011)	High technology ATD	SMART Table, Smart Board, iPad/iPod/iPhone/Mp3 Players Dynavox, Flip Page Turner, Reading Pens, Text Readers, Desktop/laptop computer (NVDA, JAWS), Tablet devices, Mobile devices, Smartphones	most intense and expensive technologies.

In addition, the accessible keyboards, speech recognition software and braille are the ATDs engaged in special education. The software and hardware development also improves the accessibility of the computer device for special students' (Albert et al., 2002). For example, Voice Finger, Freedom Scientific's JAWS, Orca are special software/hardware designed for disabled people. In Zealand, a special keyboard called LOMAK was developed for disabled students. The World Wide Web consortium understands the importance of special education and creates Web Accessibility Initiatives for disabled students. As a result, in 2012, Web Content Accessibility Guidelines were developed, thus making the content more accessible for special students.

The study conducted by Lindeblad et al. (2016) concluded that assistive technology improves the reading ability of individuals aged between 10-12 years. Smartphones and tablets are used as a platform, facilitating the learning process for the reading impaired students' (Brittney et al., 2013). The Communication Assistive Technology (CST) provides a speech-generating device for the motor and helps them participate in academic activities. Though the physical and virtual integrated augmentative manipulation and CST positively influence the education sector, it has its own drawbacks. The major drawbacks pointed out are difficulties in managing class and additional time needed by the special students to complete the task. Therefore, some strategies should be considered to improve traditional ATDs (Enarnacao et al., 2016).

In India, poverty is considered a primary challenge for implementing special education (Das & Shah, 2014). As per the United Nations Development Programme (UNDP) report 2017, the poverty rate in India reduced to half within 10 years. As per the Business Standard report 2018, per capita income in India stands at 86,647 per year and ranks 122 in Gross Domestic Products (GDP). Even if economic development is there, still poverty is rampant in India. According to the World Bank report (2017), 80% of India's poor live in rural areas.

2.5.2 Mobile-assisted civic and e-learning service

The Government of India had launched the "National e-Governance plan" campaign to empower digital technologies, improve digital infrastructure, and support Internet connectivity in India. The main aim of these digital initiatives is to provide a stable digital infrastructure service to all citizens. As a result, many general and education-related e-learning apps were introduced as a part of this scheme. For example, the civic m-learning app promotes public transparency e-service among citizens (Saxena, 2018; Sivathunu, 2018).

Social media is used as a forum to discuss opinions about m-learning apps. However, only a few studies are available for measuring the user sentiment towards m-learning apps used in civic and e-learning services (Kipsoi et al., 2012; Gullu et al., 2016; Graham et al., 2013; Nagunwa & Lwoga, 2012; Lin & Alex, 2021; Kumar & Mahendraprabu, 2021). In the present study, the Twitter sentiment analysis is carried especially on civic and education-related mobile apps, introduced through the National e-Governance Plan. The user perception towards mobile-assisted e-service is also analysed as a part of the study. The result of this study can be used to expand e-service in the mobile platform. The findings may help to improve the e-service and attract more mobile users to use these services. It will give an appropriate solution to bridge digital divide issues in India. The digital divide is often reported from India due to inadequate infrastructure and limited access to ICTs. Lower economic status and lack of digital awareness may also influence the digital divide issues (Couse & Chen, 2010). These digital initiatives aim to provide adequate infrastructure facilities and spread digital awareness among Indian citizens (Nedungadi et al., 2018).

This study confirms that the mobile platform is a better choice to promote digital awareness. This is because smartphones and tablets are portable, economical and convenient for the citizens. As evidence, the Internet and Mobile Association of India (IAMI) report (2019) stated that there is a high usage of mobile phones due to cheaper cost, faster connectivity and affordable service offered by the service provider in India (Prema et al., 2018). Furthermore, the Government also introduced the "Make in India" scheme to provide low-cost mobile phones to the citizens in their regional language (Make in India, 2019). Therefore, India is considered a suitable place to conduct this study.

This case study explores how these mobile apps improve civic as well as e-learning services and analysed digital awareness among citizens. It also enables an effective digital service to overcome digital literacy among Indian citizens. The significance of this study is to analyse the digital awareness among the citizens through social media analytics.

The mobile-assisted civic learning apps like cVIGIL, Divyang Sarathi, AgriMarket were compared with the e-learning app like SWAYAM (Study Webs of Active Learning for Young Aspiring Minds), ePathshala and E-CBSE (Electronic- Center Board of Secondary Education). Under civic learning, three different categories of mobile apps are analysed. They are the election-bound app (cVIGIL), a mobile app for special needs (Divyang Sarathi) and an agriculture-related mobile app (Agrimarket). All these applications are compared with e-learning apps. Furthermore, through social media analytics, e-service awareness and user emotions are analysed and compared. Finally, suggestions are provided for the improvement of the m-learning service.

2.5.2.1 Theoretical Background

The previous studies also confirm that m-learning platforms provide flexible and comfortable platforms to share knowledge among users (Hwang et al., 2017). Meanwhile, many government schemes promote m-learning apps for civic learning and academic learning among their citizens. For example, the Philippines government introduced an SMS learning program among users to promote m-learning services (Shiratuddin & Zaibon, 2010). On the other hand, developing countries like Japan, Malaysia and Singapore also encourage m-learning services for the learning process (Khan et al., 2015). According to the Telecom Regulatory Authority of India (TRAI, 2017) report, smartphone usage in India increases in urban and rural areas (Jehangir, 2018). Tata Consultancy Service (TCS, 2016) reported that students in India use mobile phones for their academic activities. It also states that the students use social media as a platform to learn and share knowledge. This report confirms that the usage of mobile phones will increase digital awareness among Indian citizens.

In 2008, the National Science Council of Taiwan introduced a four-year e-learning research project named “Mindtool-Assisted In-field Learning (MAIL)” to promote learning activity. This research aims to motivate students learning activities and encourage e-learning through a mobile platform (Hwang et al.,2014). The Indian Government has introduced many mobile apps to encourage civic and e-learning services among citizens. It also increases the interest of the citizens towards mobile apps. As evident, Spartak et al. (2019) conclude that the mobile application positively impacts the users. It is due to the penetration of smartphones in developing countries like India. These also create general awareness about government service, education, and entertainment (Katz et al., 2014; Grace & Umera, 2018; Sivathanu, 2019). Therefore, mobile apps are considered as an essential platform for improving civic and e-learning services (Hahn, 2014).

In general, m-learning apps has various advantages such as reachability, accessibility, and flexibility. Hence, many universities adopt the m-learning platform to promote e-learning services (Pandit et al., 2012; Hinze et al., 2017). Furthermore, the mobile apps provide anytime and anywhere service to the learners through Internet facilities. Moreover, the mobile platform is convenient for both learners and instructors for the teaching-learning process (Lai & Hwang, 2015). Thus, it enables the globalised learning platform through mobile applications. In recent years, the Government also uses the m-learning platform to promote civic and e-learning services (Seidlhofer, 2005; Dspace.dtu.ac.in, 2019).

In developing countries like Taiwan, the teaching-learning process is encouraged through the mobile platform in high school. For this purpose, the teachers from selected high schools are trained to develop the m-learning service (Lai et al., 2016). The Indian Government also launched the “Pradhan Mantri Grameen Digital Saksharta Abhiyan” scheme to create digital awareness among Indian citizens. This scheme aims to improve rural citizens’ digital literacy rate and increase job opportunities for them. As a part of this scheme, the Central Service Center is established to promote e-service in rural areas (Prema et al., 2018). Without proper awareness about the schemes, the actual benefits may not reach the target population. Therefore, social media like newspapers, television and online platforms are used to create awareness among citizens about these schemes (Hooda Nandal & Singla, 2019).

Mobile Application Download and Usage

According to Internetworldstats.com (2019), India holds second place next to China in mobile application download and usage due to the growth of smartphone users in India. More mobile apps are developed and downloaded worldwide with increased information technology and mobile phone users (Lim et al., 2014). As per the Sensor Tower report (2019), the total number of app downloads are increased between 2016-2019 App Download and Usage Statistics (2020). China was the leading market in app downloads and 45% of the global downloads with a 95 billion population. Next to Chine, India has 10% of global downloads with 20 billion people. The United States has 5% of global downloads with 12.3 billion people, followed by Brazil with 40% of international downloads with 3 billion people and Indonesia with 70% of global downloads with 2 billion people (App Download and Usage Statistics (2020), 2021.

According to App Anie stats report 2021, India is the second-largest mobile application user next to China. In 2017, the daily mobile usage hours were around 3 hours 40 minutes by Indian users, reflecting 25% among global usage. Even though India had one billion population in 2017, it held second place for worldwide app downloads. However, because 400 million hours were spent using education applications in 2019, the app download status was gradually increased to 10% of all global mobile downloads in 2019. In India, 25% of users spend more daily time with their devices (App Annie, 2021). Therefore, India is considered as one of the emerging markets in terms of mobile app usage.

Bharat Broadband Network Limited provides digital infrastructure facilities and on-demand government service to the education sector and citizens (Digitalindia.gov.in, 2019). It also facilities the high-speed Internet connection in rural areas and improved the digital literacy rate in India (Saxena 2018). Similarly, “Make in India” offered mobile phones and smartphones and increased mobile phone service availability within the country (Couse & Chen, 2010; Nedungadi et al., 2012). The previous studies reported that the mobile phone initiatives improved the socioeconomic status of Indian citizens (Rajan, 2015; Ghosh, 2017). Especially the m-learning apps attract many citizens’ attention and make them active participants in the e-service. Many social media, blogs, and posts reflect the students’ satisfaction level towards e-learning apps (Savitha & Sundar, 2016). As a result, the growth of digital learning in India is increasing (Technopak & SimploLearn, 2016).

2.5.2.2 Recent M-learning app in Civic Learning

Civic learning app will help enlighten the citizen about new government schemes, policies, and benefits (Babu, 2017; Yamada, 2011). Furthermore, according to Meihui (2000), civic learning explains the national building process and the country’s heritage to the citizens in Taiwan. This civic education apps are often important for the students and young people in an e-democracy environment. Therefore, to facilitate civic learning, mobile apps are launched by the Government of India. Some of the mobile apps discussed in this study are cVIGIL, Divyang Sarathi, and Agrimarket.

The three different domains were chosen for analysis of the awareness of civic learning. First, the mobile app cVIGIL is related to an election domain is considered. The main of this app is to avoid the violation during the election period. It also promotes awareness about the election procedures to the citizens (Gowda & Gupta, 2019). Second, the mobile app related to special education named “Divyang Sarathi” has been selected for this study. This app provides valuable information for special needs persons. The familiarity of the mobile app and the comfortableness of special users are analysed (Balaji & Kuppusamy, 2104; Haridas et al., 2018). Third, the agriculture-related mobile app Agrimarket is considered to measure the awareness level of the citizens. The primary purpose of this app is to create awareness about the current market status and commodity prices. It also provides the overall market details to the farmers of all commodities (Sarah & Virginia, 2019).

cVIGIL

The functionality of the Cvigil mobile app is described as follows. This app is effective from the date of the election announcement until the next day after polling (Election Commission of India, 2019). The complaints are registered through online photos or videos sent directly to the district control room. The "cVIGIL dispatcher," which is based on a Geographical Information System (GIS), has been turned on, and the compliant locations have been shared through navigation technology (Gowda & Gupta, 2019). The time-stamped evidence with auto location can be reported to flying squads, and action would be taken within 100 minutes. More than 10,000,000 users downloaded this app and used it during election time (ECI, 2020).

Divyang Sarathi

Divyang Sarathi is 'an accessible and comprehensive mobile app specially designed for a person with special needs' (Enabled.in, 2019). This mobile app provides information about disability acts, rules and regulations, schemes and job opportunities for disabled persons. This mobile app is launched by the Department of Empowerment of Persons with Disability as a part of the "Sugamya Bharat Abhiyan" campaign. This mobile app has additional features to convert text to audio and adjust font size according to the users' convenience. The size of this mobile app is 13MB, and more than 10,000 users download and use this app (Department of Empowerment of Persons with Disabilities, 2020)

Agri market

Ministry of Electronics and Information technology introduces Agrimarket mobile app under the scheme of "National Mobile Governance Initiatives" (Agmarknet.gov. in,2019). It gives information about the market price of crops within 50 km. Using Global Positioning System (GPS) technology, the location around 50 km is captured. The details of the market price of the different crops are displayed in the mobile app. It will help fetch some commodities' market price within a specific distance (Seva, 2019). This app also provides information about the state-wise monthly analysis report about commodities. More than 12,000 farmers downloaded this app in India and used it to know the market price and other information (Government schemes for Agriculture Extension and Technology, 2015).

2.5.2.3 Recent m-learning app in the education sector

The Global Competitiveness Report (2018) states that improving competitiveness depends on "infrastructure, higher education training, and technological readiness". "Unified Mobile Application for New-age Governance" (UMANG) program initiates many mobile apps to improve higher education (Saxena 2018; www3.weforum.org, 2019). The Government also provides sufficient bandwidth for users, adequate mobile phones, broadband subscriptions and Internet access. In addition, the Indian Government offers mobile phones and android tablets free of cost to rural citizens (Times of India, 2013; Das & Singha, 2012; Alajmi, 2014). Thus, the growth of ICTs decreases the digital divide and improves digital awareness among users. The mobile apps discussed in this study are SWAYAM, e-Pathshala, and E-CBSE.

The mobile e-learning apps considered in this study could be categorised into two divisions. First, the mobile apps that are suitable for higher education. SWAYAM and Epathshala are the two mobile apps that provide online courses to higher education students. These apps offer a well-structured and collaborative environment along with quality education. Many Indian universities provide online course content through these platforms (Pathak, 2014; Dwivedi et al., 2019; Balaji & Kuppuswamy, 2016). Second, E-CBSE which is specially designed for school students from 1 to 10 standards. Therefore, the mobile app which supports both the universities and schools are analysed in this study. The main aim of these mobile apps is to promote e-learning services to rural students. It also promotes awareness to the students about the e-learning service at the school level (Ncert.nic.in, 2019).

SWAYAM

"Study Webs of Active Learning for Young Aspiring Minds" (SWAYAM) is an e-learning platform under the "e-education" scheme. It enables an IT platform to host Massive Open Online Courses (MOOCs) in Indian universities. National Program on Technology Enhanced Learning (NPTEL) (Nptel.ac.in, 2019) is a part of SWAYAM (Swayam.gov.in, 2019) initiatives to enhance e-learning among higher education institutions**.** Several courses have been developed under the NPTEL platform. The Ministry of Human Resource Development (MHRD) supports e-learning through DTH channels with 24X7 facilities. SWAYAM plays a vital role to provide an adequate e-learning platform for online education.

This program aims to provide learning resources to all students and bridge the digital gap in India. Through education policies, it tried to enhance quality education, equality and access to digital resources. There are 203 partnering institutes involved in completing 2748 courses and 12,541,992 students enrolled in this program. The total number of students who completed the online course successfully is 6,54,664 (Swayam, 2021).

ePathshala

In India, the Union Ministry of Human Resource Developments' and the National Mission on Education through ICTs (Mhrd.gov.in, 2019) launched the "ePathshala" mobile app. 'The quality and content of the e-learning course are considered as a key component of this app. It provides open education resources to the citizens in the Indian context. The online quiz is conducted to practice and evaluates user knowledge based on online learning (Epathshala. nic.in, 2019). In the ePathshala mobile app, the e-content is developed under four quads. The first quad consists of only static e-content. The second quad has an e-tutorial in the form of video. In the third quad, the web resources are linked with case studies and other relevant information. Finally, in the fourth quad, the self-assessment is included in the quiz, assignment, and discussion in the forum'. The ePathshala mobile app aims to achieve Sustainable Development Goal 4 and bridge the digital gaps. More than 1,000,000 users download and use this app in India. (ePathshala, 2021)

E-CBSE

The Central Board of Secondary Education launched "E-CBSE" (Cbse.nic.in, 2019), a mobile e-learning app for higher secondary school students. 'This app is also launched as a part of the "National e-Governance plan". It helps students in rural areas to promote awareness about online education. It also provides a high-speed Internet connection to a rural area to bridge the digital divide issues. The e-book is also available for the students from class 1st to 10th. In addition, the National Council of Education Research and Training (NCERT) (Ncert. nic.in, 2019) enables the digital resources to the students in the rural area'. More than 67,000 users download this app for CBSE board exam preparation (ECBSE, 2021).

One of the limitations of civic learning is the lack of awareness among users. This is because only limited information is provided to the citizens about government policies, laws, and constitutions at the school level (Mulugeta, 2015; Semela et al., 2013). Endalcachew (2016) concluded that the promotion of civic learning is less in developing countries like India. Semela et al. (2013) reported that no proper mode of delivery is used in civic education. The previous studies confirmed that India is affected by the digital divide based on geographical and technical factors (Bansode and Patil, 2011, Singh, 2002). These are the main drawback identified in civic education in India. Endalcachew (2016) also concluded that the reach of civic learning is limited because of geographical constraints.

The e-learning service has the following limitations. First, the lack of users' technical skills in the online platform is the main reason to reduce the e-learning effectiveness (Willging & John, 2004). Second, the inadequate infrastructure facilities and unequal resource distribution create digital divide issues within the country (Kipsoi et al., 2012; Gullu et al., 2016). Third, the lack of technical support also reduces the user's willingness to use e-learning (Graham et al.,2013; Nagunwa & Lwoga, 2012). Finally, the lack of Internet connectivity is considered a primary reason to drop out of many online courses (Reilly et al., 2012).

In this study, the common drawback for both civic and e-learning services are identified. The two factors that affect both services are inadequate infrastructure and lack of user awareness. The m-learning apps provide flexible infrastructure services and improve awareness about civic and e-learning services to overcome these problems. These mobile platforms have connected citizens from different geographical locations and provide solutions for the digital divide issue.

The research gap identified in this study is that there are very limited studies conducted on civic learning in the Indian context. In addition, None of the previous studies has compared the user awareness level of various mobile apps used for civic and e-learning. Thus, this study is the first of its kind that compared the awareness level of citizens between the civic and e-learning service in the Indian context.

2.5.3 Cloud-Based E-learning

Many universities in developing countries focus on cloud technologies for the improvement of e-learning services. The cloud provides an asynchronous and collaborative online learning environment anywhere, anytime (Al-Samarraie & Saeed, 2018; Attaran et al., 2017). The drawback of the traditional online environment is limited storage space. Due to this problem, the response time of the learning management system also increased. Therefore, the inadequate infrastructure for the online platform is considered as the main drawback through literature. Thus the improper infrastructure reduces the system's response time and slows down the performance of the e-learning system. The features of cloud computing, including scalability, reliability, availability and performance, provides the solution for the above problem. Cloud scalability is defined as "how well the system reacts and adapt to the change." Therefore, the cloud scalability feature enables the clients to access the correct amount of resources on demand. When the number of users increased in the online platform, cloud service scales up the data storage capacity according to the need (Sharma & Kaur 2021). For example, the number of servers in the online environment can increase or decrease based on the organisation's needs.

Cloud reliability is defined as the accessibility of any resource at any time and from any location. The reliability features ensure a secure connection without any interruption and downtime. With the help of a cloud platform, the organisation can build their own fault tolerance and provide reliable service (Mayoof et al., 2021). The availability is one of the best features in the cloud, allowing users to access any products, services, or tools at any time, from any location, and on any device (Wu & Plakhtii, 2021). The availability of resources in the learning environment encourages learners to access resources from any geographical location. Hence it increases the user interest to attend and complete the online course successfully (Cheng 2021). Finally, cloud performance is the system's efficiency based on load balancing service among millions of concurrent users from multiple geographical locations (Singh et al., 2021). The system's performance is measured using parameters such as throughput, latency, load profile, number of times-outs, and error rates (Shurygine et al., 202). The major benefit of the cloud platform is that it improves the performance of e-learning services. It also provides scalable, available, and reliable service to the end-user (Wang and Jou, 2016). Compare to the traditional, cloud-based e-learning offers a better infrastructure service at a low cost. It also improves the effectiveness of online learning in a collaborative environment (Hew & Kadir 2016).

The implementation of a cloud-based e-learning system improves the efficiency of the e-learning system. The cloud-based e-learning system provides infrastructure as a service to educational institutions (Riaz & Muhammad 2015). It also reduces the implementation cost of expensive devices and increases the network transmission rate. In addition, it enables dynamic storage devices according to the number of participants in the collaborative environment (Stoffregen et al., 2016). Due to the cloud benefit, many developing countries adopt cloud-based e-learning systems. However, less adequate studies to discuss cloud-based e-learning in the Indian context and scholars are less specific in discussing the factors that influence cloud-based e-learning (Naik & Madhavi, 2015; Attaran et al., 2017; Hew & Kadir, 2016; Sharma & Kaur, 2021).

2.5.3.1 E-learning challenges

This study identifies the adoption of an e-learning system based on a cloud platform in higher education. The challenges are classified into technical, personal, organizational challenges as often reported in the literature. In this study, the Contextualized Barrier Framework (CBF) (Stoffregen et al., 2015; Deggs, 2011) is considered as an e-learning barrier framework. Based on CBF, technical challenges are analyzed (Naik & Madhavi, 2015). According to Yang and Maxwell (2011), the organizational policy framework should be considered to overcome the technical difficulties. Therefore, this study concentrates on the technical challenges faced during the e-learning implementation. The list of e-learning challenges identified is shown in Table 2.11.

Table 2.11: E-learning challenges identified in the study

Authors'	Categories	Factors	Remarks
Chawla and Joshi (2012); Mell and Grant (2021); Iqbal and Ahmad (2011)	Organizational	Inadequate Infrastructure	Hardware, software, and network device. Network connectivity speed and quality
Rao (2011)	Social	Lack of maintenance	Installation and maintenance of equipment
		Interoperability issue	Heterogeneous platform
		Low internet facilities	Unequal internet bandwidth, low speed, and connectivity

The technological barrier is classified into two categories: an organizational and social perspective. From an organizational view, inadequate infrastructure facilities and improper maintenance of the system will decrease e-learning adoption. The social perspective includes unequal access and use of Internet bandwidth, low speed, and internet connectivity. The Internet is considered an essential factor for e-learning because the availability of the bandwidth deserves the effectiveness of the online course (Charmonman et al., 2015). The poor utilization of online resources and the Internet increases the education institutions' financial crisis (Rodriguez et al., 2017). Therefore, the organization should use proper technical strategies to develop an e-learning environment.

2.5.3.2 Cloud-Based E-Learning: Selected Country Studies

Cloud computing provides online resources based on demand to the organization (Bouhnik & Marcus, 2006). The benefits of cloud computing are to reduce the implementation cost of online courses for universities. It also reduces the financial crisis of the education institution. For the service provider, the Internet is considered as a primary source to enable the cloud service. Studies are conducted in various countries to identify the factors that improve e-learning services in the cloud platform. Based on the cloud QoS (Quality of Service) parameter, the benefits of the cloud-based e-learning systems are measured. Through literature support, the countries that already adopt the e-learning system based on a cloud platform are found, and the benefits of cloud-based e-learning are analyzed.

In South Africa, the cloud service is used to bridge the digital divide gap in higher education. The cloud service is offered to this educational institution with the help of a high-speed broadband connection. This study confirmed that a cloud-based e-learning system provides a reliable and robust service to the learners (Morgan & Conboy, 2013). In Saudi Arabia, the e-learning system faces a problem due to the dynamic growth of learners. It does not have enough infrastructure to adopt an e-learning system (Okai et al., 2014). The selected country studies are shown in Table 2.12

The cloud-based e-learning system offers a solution for this problem through reliability, scalability service. It also improves the performance of the e-learning system. In the Pakistan education system, the implementation of a cloud-based e-learning system increases e-learning adoption. It automatically increases the satisfaction and performance of the learners (Nguyen et al., 2014). The universities in developing countries do not have strong infrastructure support compared to developed countries. Therefore, it is not possible to implement and maintain reliable infrastructure facilities.

Table 2.12 Cloud-based e-learning system: selected country studies

Authors	Countries	Cloud QoS parameter			
		Scalability	Reliability	Availability	Performance
Le Roux and Evans(2017)	South Africa			✓	
Alharthi et al. (2017)	Saudi Arabia	✓	✓		✓
Riaz and Sam (2015)	Pakistan			✓	✓
Stoffregen et al.,(2016)	Taiwan			✓	✓
Radenkovic et al.,(2014)	Belgrade	✓		✓	✓

But cloud-based e-learning system provides a solution to the infrastructure issues and enhances reliable service in Taiwan universities (Stoffregen et al., 2016). Radenkovic et al. (2014) identified that designing and maintaining infrastructure and providing adequate resources are complex tasks for the universities. Therefore, the University of Belgrade adopted a cloud platform to deliver infrastructure services like computing, storage and networking. The effectiveness of the e-learning system is increased in a cloud platform. Thus, the performance of e-learning is improved through reliability and scalability factors, which automatically increased the e-learning system's efficiency. Hence, many countries implement a cloud-based learning service to enhance the efficiency of online courses.

2.6 Research Gaps

E-learning plays a vital role in the modern education system. The perceived usefulness and perceived satisfaction of the learners directly influence e-learning adoption. It is necessary to consider the system and learner characteristics for developing a reliable and flexible e-learning framework. Moreover, the developing e-learning framework should be approved by National and International standards for authorizing the e-learning adoption model. Many policies and schemes were introduced in India to promote e-learning services through various platforms like SWAYAM, NPTEL, Diksha, e-Shodh Sindhu, e-Pathsala etc. The Government could also consider the e-learning dimensions and factors identified in this study, and other stakeholders are recognising the gaps in e-learning service. The literature identified that the system characteristics and learner characteristics are the most influencing factors in e-learning adoption. Recently, many academicians have reported that lack of infrastructure, poor Internet connection, lack of learners' motivation, and insufficient training for students as well as teachers are important factors in improvising the e-learning adoption model.

The research gaps identified based on the literature available in e-learning and attempted through this study are shown in Table 2.13.

Table 2.13: Research gaps

Author	Description	Remarks on the present studies
Less adequate studies reported for e-learning adoption		
Sun et al. (2008); Portz et al. (2019); Wu and Chen (2017); Urbrach and Mulller (2012); Chan et al. (2021); Lopez-Belmonte et al. (2021).	Only a few articles combine two or more IS theories to measure e-learning adoption	More than two IS theories are adopted in this study. DeLone and McLean IS model, TAM and Diffusion of Innovation theory are adopted to measure system quality, information quality, service quality, collaboration quality, perceived usefulness, perceived satisfaction and e-learning adoption.
Wang and Chiu (2011); Cidral et al. (2018); Kapoor et al. (2014); George et al. (2014); Daultani et al. (2021); Asvial et al. (2021).	Only a few studies combine learning theories to measure learner characteristics in the online environment. However, only fewer studies have been conducted on learning theories in India.	Various learning theories like social learning theory, social cognitive theory, constructivism integrated to analyse learner characteristics and technical awareness.
Fewer studies are reported on gender-based e-learning systems in the Indian context		
Huang (2013); Chan et al. (2009); Aixia and Wang (2011); Yawson and Yamoah (2021); Ouahi et al. (2021).	Scholars are less specific in describing gender-based e-learning adoption. Studies have often used gender as a	The conceptual model is framed based on feminist theory. Based on select country studies, the gender-based e-learning factors, including user behaviour, user attitude, perceived satisfaction and technology awareness have been identified and analyzed.

	moderator in e-learning studies. However, only fewer studies have been conducted on gender theories	
Less adequate studies are reported on the e-learning barrier dimension		
Abhiyendra (2007); Deursen et al. (2017); Gunkel (2003); Mariscal and Judith (2005); Zhong (2011); Shafei, Salem and Otoom (2015); Parayitam, Desai and Eason (2010); Murphy (2021); Pérez-Amaral et al. (2021)	Scholarly articles are often limited to e-learning barriers. However, the challenges faced during implementing e-learning have been inadequately discussed.	The conceptual model is developed based on the digital divide barriers factors which influence e-learning adoption was analyzed. To analyse e-learning adoption, three dimensions are integrated, and the TLB model is framed.
The m-learning platform is yet to explain its use among special education in the Indian context.		
Stevens et al. (2013); Wilson et al. (2017); Jiam et al. (2016); Chuan et al. (2018). Abuzaid (2021); Al Rawashdeh et al. (2021).	Existing articles often describe the importance of ADTs in special education. However, only less research has been conducted on special education.	Case studies have been carried out considering special school students, parents, teachers and management. The factors that influence special education, learner's awareness and usage of m-learning apps are analyzed.
Less adequate studies discuss mobile apps used in civic and e-learning services in the social media platform.		
Kipsoi et al. (2012); Gullu et al. (2016); Graham et al. (2013); Nagunwa and Lwoga (2012); Lin and Alex (2021); Kumar and Mahendraprabu (2021)	Social media is used as a forum to discuss the opinion about m-learning apps. However, only a few studies are available for measuring the user sentiment towards m-learning apps.	The case study analyses and compares mobile assist civic and e-learning service
Less adequate studies to discuss cloud-based e-learning in the Indian context		
Naik and Madhavi (2015); Attaran et al. (2017); Hew and Kadir (2016); Sharma and Kaur (2021)	Scholars are less specific in discussing the factors that influence cloud-based e-learning.	The case study included deploying two different storage setups (single and multiple data) in the CloudAnalyst simulation environment to analyse cloud-based e-learning.
Only a few e-learning frameworks are available for the Indian context.		
Vanve et al. (2016); Lahwal et al. (2016); Ang et al. (2020); Gikandi (2021)	Different types of users utilise e-learning systems for various purposes. However, only limited studies reported on types of users in the e-learning environment	Various types of users, including higher education, special school and online users, are analysed under the pedagogical dimension.

Gronlund and Islam (2010); Rao (2011); Ismaili (2017); Chen et al. (2021); Alam et al. (2021); Logan et al. (2021)	Studies have often used the technology model, e-learning success model for e-learning adoption studies. Less research has been considered on the e-learning dimension and framework.	Multiple studies, including quantitative and qualitative and case studies, have been integrated to frame suitable e-learning architecture. Various factors and dimensions have been identified to develop an eight layered e-learning framework.

As the technology adoption models used by developed countries like Norway, Denmark, Switzerland will not acclimate to the developing countries like India, there is a need to develop an e-learning adoption model suitable for the Indian context. It is also highlighted in the literature on e-learning that the digital divide is one of India's main e-learning barrier factors. The unequal distribution of online resources creates an infrastructure gap, and poor Internet connection causes the failure model. On the other hand, the factors like lack of skills, digital literacy, and prior knowledge create individual barriers and enlarge India's digital divide.

Many academicians pointed out that the success of e-learning adoption depends on the platform that promotes e-learning services. In our study, the various mobile and cloud platforms are analysed from the end-user and management perspective. Since the mobile platform is learner-centric, there is a need to create awareness and accessibility among users.

In the special education system, it is not easy to modify the traditional ATDs according to special students' needs. Therefore, special education-related mobile apps are reviewed, and the benefits of mobile apps against ATDs are studied. Special education highlights insufficient ICT skills, lack of technical awareness, and cost that reduce the special education system's efficiency. On the other hand, there is a need to study civic and e-learning apps among Indian citizens to develop a suitable learning environment. The literature also indicates that the e-learning adoption framework depends on different types of users and their attitudes. Therefore, the e-learning adoption model explains different user attitudes like higher education students, special students, and online users.

Only a few e-learning frameworks are available for the Indian context. Studies have often used the generic technology model and e-learning success model for e-learning adoption studies. Less research has been considered on identifying e-learning dimensions and developing a framework (Gronlund & Islam, 2010; Rao, 2011; Ismaili, 2017; Chen et al., 2021; Alam et al., 2021; Logan et al., 2021). Thus, this study answers the call for the development of an e-learning framework specific to Indian context

2.7 Conclusion

This chapter discussed the existing theories and empirical literature on e-learning, IS theories, learning theories, digital divide, gender-based e-learning, special education, mobile apps and e-learning adoption models. The importance and benefits of an e-learning system are pointed out through literature support. Meanwhile, IS theories are reviewed to explain how the technological factors influence e-learning systems through TAM, Delone and McLean model, Delone and McLean's model IS success model and Diffusion of innovation theory under technological dimension. On the other hand, learning theories are discussed to know how learners understand and adapt to the e-learning system. As a result, system and learner characteristics can be improved to meet learner needs while still enhancing system performance.

Education is considered as one of the key factors to measure the gender gap in the country. In this study, gender-based e-learning adoption is reviewed using feminist theory. Individual performance of the user is measured using gender theories. Based on selected country studies, the influencing factors are identified, namely user attitude, user behaviour, technology awareness, and perceived satisfaction. The literature also indicated that males' enrollment ratio is higher than that of females in higher education institutions. The gender gap index suggests that education inequality exists between male and female users in the Indian context. It explicitly denotes that India needs to improve women education by introducing new schemes and policies.

The study then reviewed the literature published on special education and identifies various dimensions of special education such as learner, student, management, government, technology and economics. The factors, including user awareness, usage and user satisfaction about the traditional ATDs, are reviewed. Meanwhile, the benefits of mobile apps in special education are examined to improve the performance of special students. The lack of user awareness concerning mobile apps in special education has been highlighted in recent studies. It is due to insufficient promotion about the benefits of mobile apps among special students. Therefore, it is a need to add influencing factors in the regulatory framework in special education.

Finally, the mobile assist e-learning service related to civic and education-related apps has been studied independently to understand the awareness and emotions of online users. It was examined because the literature suggests that mobile apps can be utilised as a platform to promote e-learning services. The mobile app's usage and awareness are reviewed from an end-user perspective.

It is also highlighted that the literature on cloud-based e-learning from the management perspective. Recent studies suggested that selecting the best service among the cloud is a challenging issue. Hence the cloud-based service, namely IaaS, is reviewed. Even though many studies have been reported on cloud-based e-learning, few studies are reported from the Indian context. Therefore, it is a need to study the cloud-based IaaS service to promote e-learning.

CHAPTER 3

RESEARCH DESIGN

Chapter 3

Research Design

3.1 Introduction

The research design approach and methodology choice for this study are discussed in this chapter, based on the research question and objectives. It discusses why India was chosen as the study location and why mixed methods research was used in this thesis.

This chapter is structured as follows. Section 3.2 presents the research question for this study, followed by a research objective in section 3.3. Section 3.4 discusses the conceptual framework and hypothesis developed for this study. Section 3.5 discusses the context and scope of the study, followed by sample size and techniques and specific research methods in section 3.6. Finally, section 3.7 concludes this chapter.

3.2 Research question

To fill the research gaps identified through the above literature review, this study addresses the following research question:

How to improve e-learning adoption in the Indian context?

3.3 Research objectives

The following study objectives were established to answer this research question and assist in the study's design, data collection, and data analysis.

Research Objective 1: To study the factors that influence e-learning adoption.

In the Indian context, the elements that influence e-learning adoption, as well as information system theories and learning theories, are inadequately addressed. This necessitates a quantitative survey to examine the system and learner characteristics.

Research Objective 2: To identify the e-learning implementation barriers in the Indian context.

A qualitative study would be ideal for addressing the above research objective as there are very few studies about e-learning barriers from a digital divide perspective.

Research Objective 3: To analyse the e-learning platforms with case studies of existing initiatives.

There is a lack of proper infrastructure and Internet as well as conceptualisation of e-learning platforms. This necessitates qualitative and quantitative study of various platforms to enhance e-learning services. First, mobile platforms used to promote e-learning service for special education students would be analysed. Then, mobile apps for civic learning and e-learning apps would be analysed from the user perspective. In addition, from management perspective, the cloud-based e-learning services for infrastructure would also be analysed.

Research Objective 4: To bring out recommendations for improving e-learning adoption.

Research Objective 5: To develop an e-learning framework to improve e-learning adoption in the Indian context.

Since there are few published papers concerning e-learning adoption among Indian users based on technology usage and learner satisfaction, a combination of case studies to address research objectives 4 and 5 would be appropriate.

These research objectives will assist in data collecting and identification of dimensions and factors influencing e-learning adoption, such as technology, learner, barrier, institution, management, and pedagogy. It will facilitate the development of an appropriate e-learning framework for the Indian context.

3.4 Conceptual framework and hypothesis design

This section will go through the study's conceptual model and the propositions for improving e-learning adoption in India.

A conceptual framework is constructed based on the previously studied theoretical and empirical foundation because this study involves qualitative interviews and a quantitative survey. Various e-learning aspects and elements were integrated into the conceptual framework (Figure 3.1) outlined for this convergent concurrent mixed method design combining multiple studies (Yin, 2008).

Propositions, rather than hypotheses, are believed to be significant in answering research questions through multiple case studies and building a framework to guide the study in generalising additional components or variables (Yin, 2008). This makes findings of the study more practical and provides substantial evidence for testing theories. The conceptual framework is shown in Figure 3.1

Proposition 1: The perceived usefulness can be improved by considering system characteristics, and the perceived satisfaction can be enhanced by considering system characteristics as well as user technology awareness.

Proposition 2**:** The e-learning adoption can be improved by the learner characteristics such as learner attitude, learner behaviour, learner confidence, and prior knowledge

Proposition 3: Gender-based e-learning adoption can be improved by considering the factors such as user attitude, user behaviour, technology awareness and perceived usefulness.

Proposition 4: E-learning adoption can be improved by reducing the e-learning barriers such as technological and individual or personal barriers.

Proposition 5: The e-learning adoption can be improved by considering the e-learning platform from management and end-user perspectives.

These prepositions, created specifically for this study, interpret the relationship as unidirectional and confine it. It can, however, be reinforcing and related, but this was not taken into consideration in this study.

Dependent variables

The dependent variable is the variable that is influenced by the independent variable (Lee et al., 2009, Eom et al., 2018). It is the variable that is observed and measured to identify the effects of independent variables. The following three dependent variables were used in this study:

- Perceived usefulness
- Perceived satisfaction
- E-learning Adoption

Independent variables (Explanatory variable)

- The main factor that users want to study is the independent variable. It is the variable that the researcher chooses, manipulates, and measures its effect. The focus of

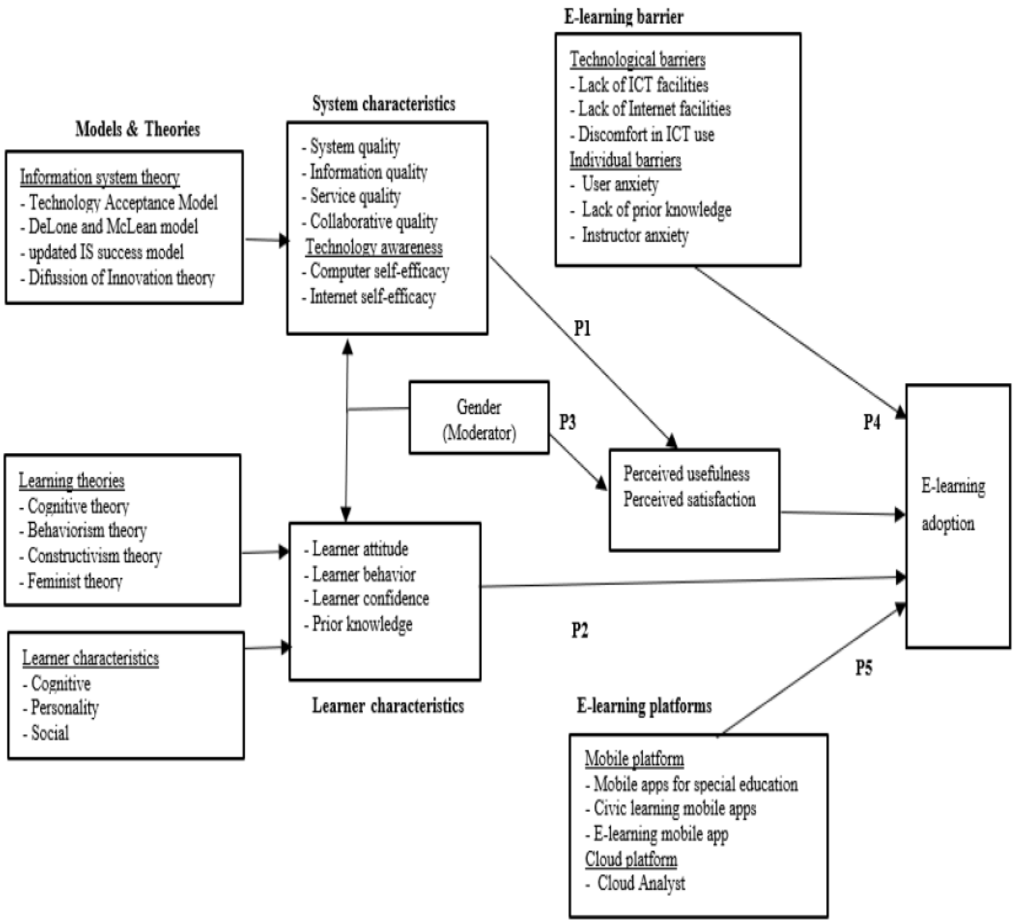


Figure 3.1: Conceptual Framework

independent variables is their direct relationship to the dependent variable (Meyen et al., 2002; Kothari, 2004; Saba, 2012). The figure shows the constructs and independent variables adopted in this study.

Table 3.1 Independent variables

Constructs	Independent variables
System characteristics, Technology awareness	System quality, Information quality, Service quality, Collaboration quality, Internet facilities, Computer self-efficacy, Internet self-efficacy
Learner characteristics	Learner attitude, Learner behaviour, Learner confidence, prior knowledge
e-learning barrier	Lack of ICT, Lack of Internet facilities Lack of prior knowledge, user anxiety, lack of prior knowledge, Instructor anxiety

As illustrated, these were defined for each factor in the study. Gender acts as a moderator to predict the e-learning adoption among users in the Indian context.

3.5 Operational Definition

Information system theories connect general system theories with information technology and build a prototype that fulfils specific objectives. The information system for e-learning system is designed using several theories and standard guidelines. The development of the e-learning technology dimension is influenced by several information system theories, including Technology Acceptance Model (Davis et al., 1992; Fakhoury & Aubert, 2017). DeLone and McLean model (DeLone & McLean 2003), updated IS success model (DeLone & McLean, 2004; Al-Mamary, Shamsuddin & Aziati, 2014), and Diffusion of Innovation theory (Rogers, 1995; Pinho et al., 2021) with each theory having different dimensions (Ray et al., 2019; Shim et al., 2018).

Learning theories describe how learners learn, understand, and enhance their learning skills (Beard et al., 2007; Kibuku et al., 2020). Some of the major learning theories are cognitive theory (Bagchi, 2005; Hargittai & Shafer, 2006; Hermeking 2006; Wang & Newlin, 2002), behaviourism theory (Ertmer et al., 2020; Ahmad et al., 2020), constructivism theory (Paul et al., 2021; Azhari et al., 2020) and feminist theory (Meßmer & Schmitz 2004; Hughes, 2007). Learning theories assist in developing frameworks based on learners' needs and making more informed decisions regarding the best learning strategies.

The operational definitions for the factors that influence e-learning adoption are summarised in this study and shown in Table 3.2.

Table 3.2: Operational Definition

Factors	Operational Definition
System characteristics	It is an attribute that determines the characteristics of a system, such as system quality, information quality, service quality, and collaboration quality.
Learner characteristics	Characteristics of the learner are determined by their attitude, behaviour, confidence, and prior understanding of the online course.
Perceived usefulness	It is up to the individual to believe that the e-learning system will help them improve their performance.

Perceived satisfaction	It is defined as a user's acceptance of an e-learning system's comfort of use.
Technological barrier	The lack of ICTs and inadequate internet facilities creates a technological barrier during the adoption of e-learning.
Individual barrier	Individual barriers are created by a lack of digital literacy, user anxiety, and prior knowledge.
Mobile platform	The mobile platform allows for a more flexible learning environment while also bridging the gap between students and instructors
Cloud platform	It promotes scalability, reliability, and resource availability in the online environment by enabling infrastructure services on demand.

3.6 Context and Scope of the Study

The context of a study describes its background elements, such as "where", "what", "who", and "when" it was conducted. On the other hand, the scope of a study describes the research topic and its specific aspects that are being investigated. Overall, this section explains why and how this study has been carried out in India.

3.6.1 Justification for the Indian context

The justification for the study conducted in India is as follows:

First, more than 50% of India's population is under the age of 25 (Sharma, 2020), and more than 65 % is under the age of 35, with an average age of 29 years out of the total population**.** According to Brandfinance.com, India is the second-largest country for online course enrollment, after the United States (2019). Indian students seek to increase their learning abilities by participating in an interactive learning environment (Yuen & Ma, 2008). According to the students, e-learning has helped them overcome geographical and financial limitations while providing higher-quality education (Ilin, 2020). As evidence, India has a higher number of students enrolled in online courses (Sharma, 2020). Second, India has a high Internet penetration rate. According to Internetworldstats.com (2019), India is ranked second behind China. It is due to the increasing number of smartphone users in India (Nagaraj et al., 2021). The availability of Internet bandwidth, low-cost data plans, and government awareness efforts are the other factors found in this study (The Economic Times, 2019).

Third, the Government is encouraging schools and higher education institutions to utilise digital and multimedia technology. Through the 'Digital India Campaign,' the Government encourages digital awareness among school and higher education students (Nedungadi et al., 2017). 22 new initiatives have been launched recently to broaden the scope of the Digital India programme. These initiatives included projects in digital infrastructure and industry promotion to reach universal digital literacy and to provide universal access to digital resources (Varekar, 2021). As a result, it raises the digital literacy rate and encourages users to adopt online courses (Bharucha, 2018).

In the year 2021, there would be 51 central universities, 397 state public universities, 334 state private universities, 3 institutes founded under state legislation, and 126 institutions deemed to be universities according to the University Grants Commission. As a result, the rapid growth of educational institutions needs increased staffing and technical resources. Furthermore, rapid technological innovations result in a knowledge gap between teachers and users. It creates a significant need for qualified teachers or experts in the education sector, especially in higher education institutions (Nneka Eke, 2010).

However, the adoption of ICTs in education is more than the enrollment rate and differ by regional variants. Therefore, the current study is conducted in the Indian context. The enrolment ratio of male and female students in schools and higher education institutions are represented by the Gender Gap Index value. In 2018 Gender Inequality Index, India was ranked 108 in educational attainment and 147 in gender inequality (World Economic Forum, 2019).

The Gender Gap Index value shows the enrollment ratio of male and female students in the schools and higher education institutions. India was ranked 108 in educational attainment and got 147th rank in the Gender Inequality Index, 2018 (World Economic Forum, 2019). In addition, the Human Development Index shows that female development is lower than male development in the Indian context. It indicates that gender inequality exists in Indian schools and universities.

In developing countries like India, separate policies and schemes are introduced for the improvement of special children. According to the Education Law for the disabled, article 29 (2) provides that "no disabled citizen shall be denied admission based on religion, caste, race or language". Article 45 also implements that the state should provide compulsory and free education for all children, including the disabled, until 14 years. According to the United Nations Children's Fund (UNICEF) report 2017, it has introduced development plans across India since 1949. The Anganwadi workers in 18,000 centres support primary school students in India. In addition, the State Council of Educational Research and Training and the District Institute of Education and Training focus on the teaching-learning process with specific technical support. It has also strengthened child-friendly pedagogy, integration of ICTs and teacher educator capacities in India.

Along with the Government policies, Assistive Technology Device (ATD) was introduced in the modern education system for special education. Assistive technology helps to bridge the learning environment with disabled students. According to the Individuals with Disabilities Education Act, 1990 section 300.5 states that "the assistive technology device is a piece of equipment that is modified and used to improve functional capabilities of a child with a disability" (Mechling 2007). According to the individual needs, ATD is modified to overcome the difficulties faced by disabled students (Encarnaco et al., 2016).

Even though the ADT has improved special education in many ways, it remains unreachable for a large number of disabled students. Developing countries like India have limitations like availability and affordability (Ismaili 2017). Therefore, mobile learning is introduced as an alternative solution to overcome limitations (Godwin, 2011). In this study, m-learning using smartphones and tablets are considered as an alternative learning tool for ATD. The various m-learning applications compared with the ATDs at the level of availability, affordability and other factors. The comparison is made relevant in the case of physical and mental disabilities as well. In the past decades, special groups face communication problems within the school and society. Mobile application developers do not consider this a special group, but many organisations concentrated on special needs students (Anuar et al., 2014).

As a result, many mobile gadgets with open-source apps are introduced as alternative monofunctional ADTs in the formal and informational learning platforms. According to Hulme and Shield (2008), mobile is treated as a mediating device that promotes e-learning anywhere and anytime. This special feature enables the growth of m-learning in special education. As a result, the research team of the University of Granada and the University of Murcia deployed a mobile platform in iPad and iPod devices to provide m-learning for special need students (Fernandez et al., 2013). In addition, the Google play store consists of many mobile apps for special students. Ismaili (2017) concluded that mobile apps had satisfied the student with special needs. It also ensures that these mobile apps provide availability and affordability service to disabled students. Meanwhile, the increasing number of open-source mobile apps also confuses special students to choose the correct application. Therefore, this study identified the different types of mobile apps for disabled students.

According to the Telecom Regulatory Authority of India (TRAI, 2017) report, smartphone usage in India increases in urban and rural areas (Jehangir, 2018). Tata Consultancy Service (TCS, 2016) reported that students in India use mobile phones for their academic activities. It also states that the students use social media as a platform to learn and share knowledge. This report confirms that the usage of mobile phones will increase digital awareness among Indian citizens.

The Indian Government has introduced many mobile apps to encourage civic and e-learning services among citizens. It also increases the interest of the citizens towards mobile apps. As evident, Spartak et al. (2019) conclude that the mobile application positively impacts the users. It is due to the penetration of smartphones in developing countries like India. These also create general awareness about government service, education, and entertainment (Katz et al., 2014; Grace & Umera, 2018; Sivathanu, 2019). Therefore, mobile apps are considered as an essential platform for improving civic and e-learning services (Hahn, 2014).

In general, m-learning apps has various advantages such as reachability, accessibility, and flexibility. Hence, many universities adopt the m-learning platform to promote e-learning services (Pandit et al., 2012; Hinze et al., 2017). Furthermore, the mobile apps provide anytime and anywhere service to the learners through Internet facilities. Moreover, the mobile platform is convenient for both learners and instructors for the teaching-learning process (Lai & Hwang, 2015). Thus, it enables the globalised learning platform through mobile applications. In recent years, the Government also uses the m-learning platform to promote civic and e-learning services (Seidlhofer, 2005; Dspace.dtu.ac.in, 2019).

The Indian Government also launched the “Pradhan Mantri Grameen Digital Saksharta Abhiyan” scheme to create digital awareness among Indian citizens. This scheme aims to improve rural citizens’ digital literacy rate and increase job opportunities for them. As a part of this scheme, the Central Service Center is established to promote e-service in rural areas (Prema et al., 2018). Without proper awareness about the schemes, the actual benefits may not reach the target population. Therefore, it is necessary to conduct the study on how the mobile platform helps to promote e-learning services among Indian citizen.

Finally, the most important drawback of the traditional online environment is the lack of storage space from the management perspective. The response time of the learning management system has also increased as a result of this issue. The e-learning system performance is automatically reduced due to this problem. On the other hand, deploying an e-learning system on a cloud platform will improve the system performance due to its scalability, reliability, flexibility, and reliability. It also reduces the cost of implementing expensive devices and speeds up network transmission.

The comprehensive literature review found that there is a dearth of studies that combined information and learning theories to determine the factors impacting e-learning adoption. The same was even more evident in the Indian context. Lack of infrastructure facilities (Abhiyendra, 2007; Deursen et al., 2017), inadequate Internet facilities (Gunkel, 2003; Mariscal and Judith 2005; Zhong, 2011), unequal distribution of ICTs (Bagchi 2005; Hermeking, 2006; Hargittai, 2001), lack of digital literacy (Dijk, 2003, Lee et al., 2014, Pearce and Rice 2013), user anxiety (Van et al., 2017, Kassab, Shafei, Salem & Otoom 2015) and lack of prior knowledge about e-learning (Parayitam, Desai & Eason, 2010; Eunjin et al., 2009) were identified as various factors that reduced the effectiveness of e-learning system.

3.6.2 The Scope of the Study

The current study considered various dimensions and factors of the e-learning system in the Indian context. In developing countries, e-learning success was measured using the factors like computer training (Xaymoungkhoun et al., 2012), computer self-efficacy (Simmering et al., 2009; Pellas 2014), perceived usefulness (Davis 1998; Elkaseh et al.,2016) and learner attitude (Zhao et al., 2021; Ntshwarang et al., 2021). Overall, the e-learning challenges faced by developing and developed countries are the same, but more research focuses on the technology dimension in developing countries. At the same time, the developed countries focus on the learner dimensions (Andersson & Grönlund, 2009). Therefore, there exists a lack of research articles about e-learning adoption in the Indian context. Thus, the scope of the study is limited to:

- assessment and identification of factors facing e-learning implementation at higher education institutions in India. Here, the assumption was that key issues/ factors affecting the successful performance of e-learning lead to improved learning-teaching delivery to the students. Hence the e-learning dimensions and factors do affect e-learning adoption in the Indian context.
- researches and contribution of information system theories and learning theories

were inadequate in the Indian context

- Gender-based e-learning study is established on feminist theory and emphasises the relevance of women's education in India, which is under-reported.
- Identify the barrier factors that affect e-learning adoption among Indian users and improve the e-learning framework in the barrier dimension.
- Social media users are aware of the benefits of mobile apps and how the mobile apps would help with civic and e-learning services.
- Educational needs and technological availability of special students and influencing factors are identified, and the solutions are provided through mobile platforms.
- The cloud-based e-learning environment is deployed, and the infrastructure service (data storage) is analysed. The overall response time is compared between two data centre models.
- The study was done only in India and at the selected universities and higher learning institutions present in the Southern region because of the convenience for the researcher to easily collect data at a minimum cost. The presence of the intended respondents, time limit, and financial problems were the reasons why the selected area was an important and necessary area for this study.
- Students from higher education institutions, online users and special schools are involved in the study to collect their opinion about the system for improving e-learning adoption in the Indian context.
- Published journal articles and conference proceedings of e-learning framework and adoption.

3.7 Research Methodology

Mixed method research is defined as collecting and integrating qualitative and quantitative data in a study utilising different designs that may include philosophical assumptions and theoretical frameworks (Creswell, 2014). In the disciplines of social sciences (Teddlie & Tashakkori, 2009; Bryman, 2016), management (Abro et al., 2015), and accounting (Grafton et al., 2015), it has been widely used. Many educational researchers have recently moved away from the traditional purist research method that used either a qualitative or quantitative technique alone. Instead, the academics attempted to mix both approaches in the research review, mixing features of both traditions at various stages of the experimental investigation, such as the development of research questions/hypotheses, research method design, data analysis, and research findings discussion. An empirically validated study design is supported by such integration, which utilises the strengths of both traditions. In addition, because of the scope of the research limitations highlighted in the previous chapter (chapter 2), this thesis used mixed-method research to answer the research question, “How to improve e-learning adoption in the Indian context?”

This thesis utilises convergent concurrent mixed-method design and analytic processes (Kerrigan, 2014) based on the research topic. Both quantitative data (questionnaire survey, simulation) and qualitative data (interview-based case study and Twitter data) were collected simultaneously. The researcher could use a mixed-method design to combine data from different stages of the project during interpretation.

3.7.1 The Methodological Choice in this Thesis

In this study, mixed-method research was used to analyse e-learning adoption through convergent concurrent mixed-method design. The convergent concurrent mixed method design is used to analyse quantitative and qualitative data separately and integrate different results are during interpretation. Schelfhaudt and Crittenden (2005) used this approach to collect qualitative data from business school teachers and qualitative data from business school students. Given the above consideration, it was decided to use a convergent concurrent mixed method design wherein the findings from the quantitative and qualitative methods could be integrated.

This analysis includes i) a quantitative questionnaire survey of higher education students to determine the factors that influence e-learning adoption; ii) a quantitative questionnaire survey of higher education students to determine the factors that disrupt e-learning adoption; iii) qualitative data extracted from social media to determine the most prominent e-learning barrier factors; iv) qualitative data extracted from special school students and staff to compare traditional ATDs with mobile apps; iv) qualitative data extracted from social media to identify the use of mobile apps for e-learning and civic learning; v) quantitative approach to evaluate infrastructure services in the cloud-based e-learning environment. Figure 3.2 illustrates the Research Design-Convergent Concurrent Mixed-method Design.

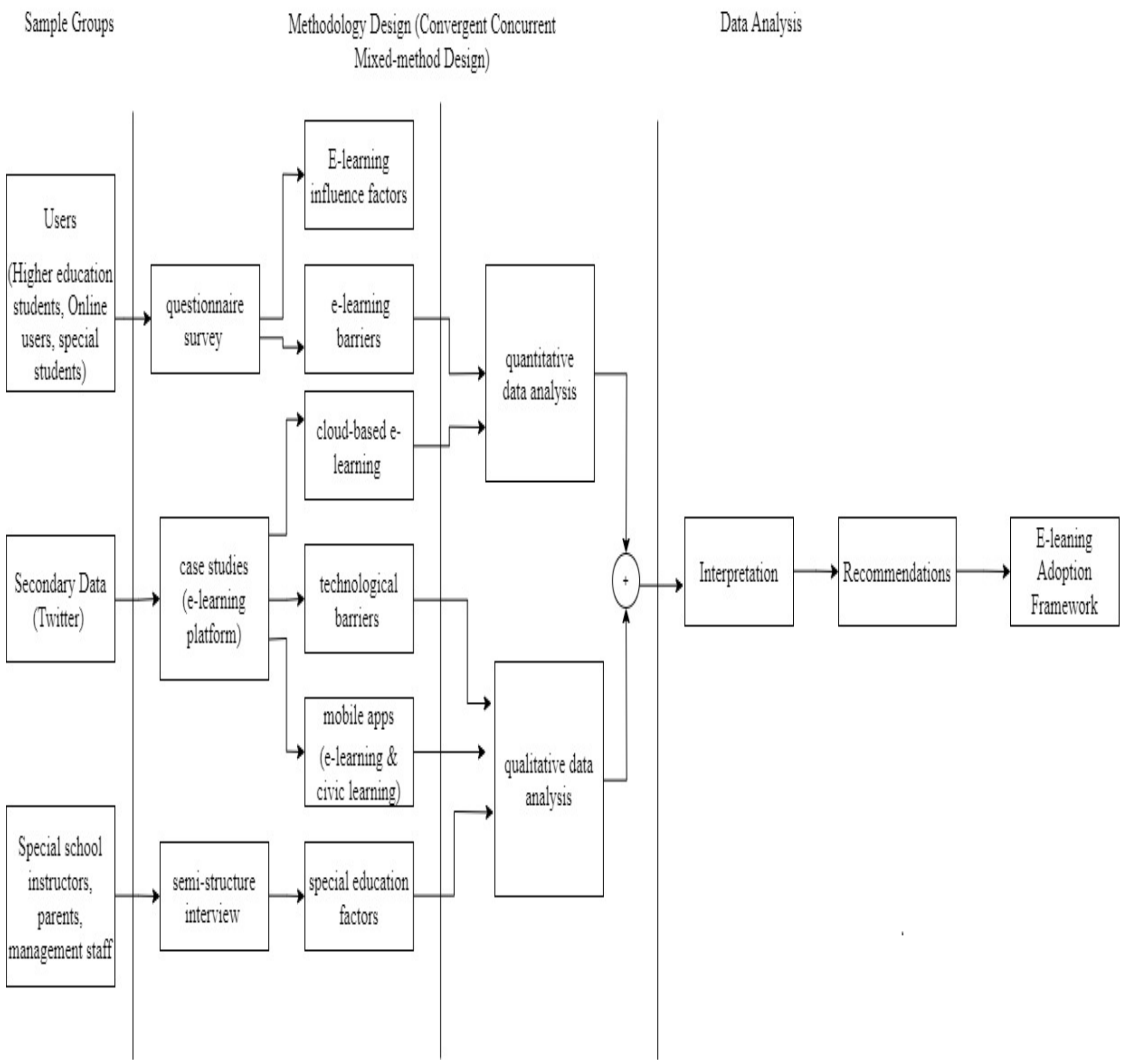


Figure 3.2 Research Design-Convergent Concurrent Mixed-method Design

The mixed-method approach is used when researchers use two or more different approaches among different respondent groups simultaneously. Higher education students, Internet users, special students, special school teachers, and management staff are all involved in our research. Since data is collected concurrently from multiple stakeholders, both approaches have the advantage of collecting data simultaneously. Thus, a convergent concurrent mixed-method design is essential in this analysis.

3.7.2 The Justification for Mixed Method Research

The researcher must examine the methodological option when performing research. The resources available and conceptual beliefs about modern science and society influence it (Gill & Johnson, 2002). The adoption of mixed-method research in this study is influenced not only by the gaps found in the literature review but also by the topic's practicality in e-learning and information systems. It is essential to introduce the study's research history before beginning with the methodology choice.

Although numerous e-learning systems have been used to improve the education system, there is a lack of quantitative research that analyses the factors of e-learning systems in the Indian context, as indicated in chapter two. To further understand, the study is listed as follows. First, the previous literature on system attributes, learner characteristics, and factors impacting e-learning adoption has been considered. Second, the study examined the gender differences in e-learning adoption and the identified determinants based on selected country studies. Third, the study highlighted e-learning challenges such as technological and individual barriers that may impact e-learning adoption in India. Fourth, 43 respondents, including special students, parents, instructors, and management, were interviewed in semi-structured qualitative interviews to confirm the identified factors influencing e-learning services using a mobile platform. Fifth, a qualitative analysis is conducted using the Twitter database to determine user awareness about mobile assist e-learning. Sixth, the case study will be used to examine cloud-based e-learning services from a management viewpoint. Finally, the outcomes of each strategy were triangulated, and a proposal for an "e-learning adoption framework" for the Indian context was developed. However, it has been determined that India's infrastructural services for promoting e-learning are insufficient. Individual barriers are also created by a lack of digital awareness and prior experience of e-learning. In this case, data was collected from users through an online and offline questionnaire survey, and quantitative analysis has been performed.

Special education aims to design instruction, support and service according to the unique learning need of the special student. As per World Health Organization (WHO), Intellectual property affects two functional areas: intellectual and adaptive functioning. According to Ghaleb (2019), the coordinating method will help disabled students' social and behavioural characteristics. Many types of research have been conducted to analyse the use of assistive technology-enhanced learning with a group of disabled students. However, only a few types of research have been done with the global standard. It was also noted that there is an inadequacy of quantitative research that explains the factors that affect special education in the Indian context. Therefore, it is necessary to upgrade the modern education system for special students with assistive technology devices and mobile learning technologies (Mechling, 2007).

3.8 Questionnaire Design and Administration

To address the research question of *"How to improve the e-learning adoption in the Indian context?*" this study considers various e-learning dimensions (technological dimension, learner dimension, barrier dimension) and factors that influence e-learning adoption (Uppal et al.,2017; Cidral et al., 2018). These are the study's research objectives, which were prepared and conducted using the questionnaire.

3.8.1 Questionnaire survey

The importance of e-learning and mobile assist e-learning apps for promoting e-learning adoption has been identified in various literature. However, only a few quantitative research addressing learner dimensions and learning theories have been described. Furthermore, only a few studies have reported on the various dimensions of the e-learning framework. As a result, this study uses descriptive statistics to fill in the gaps: It involves collecting information from Indian higher education students to determine the e-learning system's perceived usefulness and learners' perceived satisfaction. Hypothesis Testing: It includes factors identified in the prior literature based on information system and learning theories and an e-learning adoption examining the perceived usefulness and perceived satisfaction.

Descriptive Statistics

A study was conducted to measure e-learning system quality, learner awareness and satisfaction, and to analyse platforms that promote e-learning among users from November 2018 to April 2019. Participants were selected based on convenience and purposive sampling. The former was used to collect responses from engineering students, and the latter was used for specific situations. A pre-tested questionnaire was designed using existing literature (Kayyali et al., 2017; Parthaje et al., 2016; Ehteshami et al., 2013; Khatun et al., 2014; Atulomah et al., 2010). The items for the questionnaire were adopted, modified, and developed by reviewing different research studies. Based on the expert suggestions, changes were made and pre-tested with a group of 20 PhD scholars to ensure clarity. During this period, wordings were altered as needed, and unclear questions in the instrument were explained. The survey's final items are listed in Appendices A.

Hypothesis Testing: Perceived usefulness

The construct system quality was measured using three items (Urbach et al., 2010; Cidral et al., 2018). These factors are adopted from Delone and McLean IS success model to measure the quality of the e-learning system, which is considered a critical factor for e-learning adoption (Sun et al.,2008). The information quality is measured using three items adapted from Delone and McLean IS success model (DeLone & McLean, 2003; Gable et al., 2018). The service quality is measured using three items adapted from the Delone and McLean IS (Aparicio et al., 2017). The last parameter that determines the system characteristics is collaboration quality is adopted from Cidral et al. (2018) and used measured collaborative service using three items.

Computer self-efficacy consist of four items to determine the user computer awareness based on social learning theory (Hargittai & Shafer, 2006; Chopra & Madan, 2021; Rahmah et al., 2021). In addition, Internet self-efficacy is added in the model with three items that determine the user's Internet knowledge based on social cognitive theory (Parkes et al., 2015). Based on these factors, the perceived usefulness of e-learning is analysed, which directly influence e-learning adoption in the model.

Perceived satisfaction

The system characteristics consist of four constructs: system quality, information quality, service quality, and collaboration quality which influence perceived satisfaction. In addition, computer self-efficacy consists of four items to determine the user computer awareness based on social learning theory (Hussin & Ahmad, 2021; Vélez & Gweon, 2021). Finally, Internet self-efficacy is added in the model with three items and determine the user's Internet knowledge based on social cognitive theory (Hamdan et al., 2021; El-Sayad et al., 2021). The perceived satisfaction consists of three items that measure learner satisfaction. In this study, the e-learning adoption is analysed using perceived satisfaction constructs.

Learner characteristics

For measuring learners characteristics in the e-learning environment, the learning theories such as social cognitive theory, constructivism, feminist theories were utilised. The learner characteristics (Passerini & Granger, 2000; Vreede & Mgaya, 2006) is determined based on four three constructs: learner attitude, learner behaviour, learner confidence and learner prior knowledge. First, the learner attitude (Arbaugh, 2002) consists of three items to measure the beliefs, interests and motivation of the learners. Second, the learner behaviour measures trust, performance expectancy and practice of the learner in the e-learning platform (Venkatesh et al., 2003; Liu & Feng, 2011). Third, the learner confidence (Moore et al., 2011) construct measures internal influence, social collaboration, and learners' perceptions about the e-learning system. Finally, prior knowledge (Jacobsen, 2019; Jeong Kim et al., 2012) about the online course is measured using three items: familiarity, knowledge acquisition, and implication.

Gender as moderator

Gender is considered as a moderator in this study. The individual performance of the user is analysed with three constructs: user attitude, technology awareness, perceived satisfaction using cognitive constructivism learning theory (Meßmer & Schmitz, 2004; Nahl, 1998; Bystrom, 2000). The construct 'user attitude' (Abidin et al., 2018; Barkatsas et al., 2009) was measured using three items, and 'technology awareness' (Jaiyeoba & Iloanya 2019; Folorunso et al., 2006) was measured using four constructs. The construct 'perceived satisfaction' consists of five items that measure learner satisfaction, and it is adopted from Liaw (2008) and Liaw and Huang (2013). Finally, the 'social behaviour' of the user is measured using four items (Palincsar, 1998; Gruender, 1996) based on social constructivism (Cornu & Peters, 2005; Connaly & Begg, 2006)

E-learning barriers

The construct 'technological barrier' was measured using three constructs lack of ICTs facilities (Abhiyendra Kumar, 2007; Deursen et al., 2017), lack of Internet (Bagchi, 2005; Zhong, 2011) and discomfort in ICTs use (Hermeking, 2006; Hyman, 2012). The construct is taken from the literature (Upadhyaya, 2013; Chou, 2001; Josephine et al.,2017). The construct 'technological barrier' directly influences e-learning adoption. Items for 'individual barrier' was measured with three items adapted from Parayitam et al. (2010) and Eunjin et al. (2009) and slightly modified according to the study context.

Cloud platform

To improve e-learning services, several institutions in developing nations such as India are focusing on cloud technologies. The cloud provides an asynchronous and collaborative online learning environment where users can access services from anywhere at any time (Attaran et al., 2017; A-Samarraie & Saeed, 2018). The advantage of the cloud over the online course increases the efficiency of an e-learning service. It also provides the end-user with a scalable and reliable solution (Wang & Jou 2016). In comparison with traditional e-learning, the cloud offers a more cost-effective infrastructure solution. It also enhances the efficacy of online learning in a collaborative setting.

3.8.2 Interview-based case study

A qualitative approach has been followed to address the two research questions: Firstly, what factors influence special education in India? Secondly, How to improve special education using mobile apps? Qualitative data helps describe the phenomenon by exploring key events, practices, and underlying reasons (Mousavi & Bossink, 2017).

Mobile learning

Previous studies reported that the mobile platform is a better solution for promoting digital awareness (Uzunboylu et al., 2009; Alzaza & Yaakub, 2011; Khan et al., 2015). This is because smartphones and tablets are portable, cost-effective, and convenient for users. As evidence, the Internet and Mobile Association of India (IAMI) study (2019) stated that mobile phones are widely used in India due to lower costs, faster connectivity, and affordable service provided by the service providers (Nedungadi et al., 2018). In addition, the government launched the "Make in India" programme, which aims to offer residents low-cost mobile phones that are available in their native language (Make in India, 2019). As a result, India is thought to be a suitable place to perform this research.

This case study explores how these mobile apps enhance civics and e-learning services as well as individuals' digital awareness. It also enables an effective digital service that helps Indian citizens overcome their lack of digital literacy. The focus of this research would be to use social media analytics to examine citizens' digital awareness. As an outcome, the research question is formulated as "*How do mobile platforms promote civic learning and e-learning service among Indian citizens*?"

Special Education

The Rehabilitation Council of India Act 1992 highlights the first legislation related to special education, which defines the minimum standard of education as mandatory for the person with a disability. In addition, the Rights of PWDs Act which is enforced in 2016, defines a person with a disability has the right to participate equally in society. To enhance the standard of a disabled person, the Government of India integrates disabled persons with special education and create a suitable learning environment according to their needs.

The previous researchers pointed out that the lack of financial support is considered one of the main drawbacks of special education. It is because most of the learning environment is designed according to special needs. Due to insufficient funds, many special schools cannot develop the IEP as per special student needs. In addition, the availability and usability of the traditional assistive device are also limited due to the cost factor. Therefore, the awareness about the availability of conventional assistive devices is low among special institutions. Moreover, in India, there is no proper coordinating system available in special schools. Most of the institutions do not follow appropriate assessment and planning strategies. Therefore, it is necessary to conduct this study in the Indian context.

More than 2.1 % of the population were disabled in India, and more than 65% lived in rural areas. A purposive-convenient sampling method was used to select study locations and interview respondents. This study selected special schools and colleges from the Southern part of India, especially Tamil Nadu and Kerala because for the following reasons. In Tamil Nadu, out of the 7,21,47,030 total population, 11,79,963 were disabled, and the percentage of the disabled population is 1.64%. According to the statics report 2018, disabled persons who completed their secondary education is 23.8% for males and 13.9% for females. The literacy rate of Tamil Nadu is 80.33%, and the literacy rate of disabled people is 60.66%. Moreover, the number of special education colleges (43) are more in Tamil Nadu than in other states in India.

Kerala has the highest literacy rate among disabled people in India. Moreover, the percentage of disabled people attending education institutions is high in Kerala. The total population of Kerala is 3,34,06,061, and the people of the disabled population is 7,61,843, and the percentage of the disabled population is 2.28%. In Kerala, the literacy rate of the total population is 93.91%, and the literacy rate of disabled persons is 70.79%. In addition, the number of special education colleges in Kerala is 29. Therefore, the special education college from Tamil Nadu and Kerala is chosen for this special education study.

The growth of ICTs enriches special education by integrating the technology according to the special students' needs (Aresti et al., 2014). The ATDs tools play a vital role in the special education environment. The study aims to identify various special education dimensions such as technology dimension (Waetjen, 1995; Jennings et al., 2012), individual dimension (Opertti et al., 2013; Macfarlane, 2002), school dimension (Reynolds, 2002; Belmonte & Cranston, 2009), government dimension (Shabaya et al., 2004; Mantle et al., 2006), teacher dimension (Park et al., 2019) and an economic dimension (Possi, 2019; Baykoc et al., 2012). Special education is an influential tool that empowers people with disabilities. Therefore, various dimensions and factors are included in this research. Article 21A of the Constitution states that education for disabled students is a fundamental right. In addition, the Person with Disability Act ensures that education is free and compulsory for a disabled person under the age of 18. In 2010, the Government of India launched a program called "Shiksha Abhiyan" to educate disabled children under the age of 6-14 years. In addition, the Integrated Education for Disabled Children (IEDC) scheme provides free education for disabled students in the age group of 15-18 years.

3.8.3 Justification for Social Media Analytics

Six Degrees was the first social media website launched in 1997, where users can upload their profiles and make friends. Later in 1999, the blogging platform became more popular and recognised by many users to publish blogs and web pages. Social media helps to share opinions, ideas and knowledge and allow connecting with potential professionals. Facebook and Twitter were created in 2006 due to this social media phenomenon, and they connect individuals worldwide. Twitter is a microblogging platform where users can send and receive posts, follow other users, create tweets and retweet. Twitter is primarily used by smartphone users who do not wish to read long content items on-screen. Academics, students, policymakers, politicians, and the general public have become increasingly interested in Twitter (Singh et al., 2018; Chan & Guillet, 2011; Stephen & Galak, 2010; Trainor et al., 2014; Tess, 2013; King et al., 2013).

Sentiment analysis is one of the most often utilised social media analytics for determining public opinion. Each tweet in the Twitter database approximately consists of 0.47 emotion tokens from the statement (Suresh & Raj, 2019; Liu & Zhang, 2012). These emotion tokens reflect the users' feedback on the social media platform (Jamali et al., 2019). As a result of these advantages, academics, scholars, students, and policymakers began to use social media to understand better education-related services and governance (Lee & Kwak, 2012). The use of Twitter in educational research is recognised as a developing subject of study. Researchers have utilised Twitter to analyse user opinions regarding education-related mobile services. For example, through its social media webpages, the Twitter website for e-learning keeps users informed about various civics learning and e-learning-related apps.

The availability of a vast amount of data on the Internet and social media has increased the importance of data analytics among researchers and academicians. This research uses social media analytics for e-learning-related services, mobile apps, and sentiment analysis to evaluate specific themes that people are concerned about.

3.9 Conclusion

This chapter provides detailed descriptions of the researcher's methodological decision and the general procedures for collecting, analysing, interpreting, and reporting data. The researcher believes that using a convergent concurrent mixed-method design that combines qualitative and quantitative data will help compare study findings and enhance the overall research validity.

This chapter outlined the overall procedure used in this research. To begin, it has provided the study research topics and objectives. Second, the conceptual framework and hypothesis for executing convergent concurrent mixed method design were discussed. Third, this chapter introduces the study framework and scope. Finally, the justification for the methodological decision was discussed. To answer the research question, it was chosen to utilise a convergent concurrent mixed-method design, in which the findings from quantitative (questionnaire survey) as well as qualitative (interview-based case study and Twitter data) approaches were combined.

C H A P T E R 4

QUANTITATIVE STUDY

Chapter 4

Quantitative Study

4.1 Introduction

This chapter explains the purpose of the quantitative analysis conducted in this study. First, the factors that influence e-learning adoption are analysed. Various information system theories and learning theories are utilised to identify those factors. Second, gender-based e-learning adoption is analysed based on select country studies. Third, the different types of barriers that reduce e-learning adoption are recognised and analysed through empirical analysis. Fourth, the cloud platform is deployed through the CloudAnalyst simulator, and the performance of cloud-based e-learning is analysed. This quantitative study examined the e-learning adoption factors, gender-based e-learning study, e-learning barriers and cloud-based e-learning systems (research objectives 1 and 2).

To accomplish the purpose of this chapter, it is arranged as follows. Section 4.2 provides research design of factors that influence e-learning adoption, descriptive statistics of the data collected from the questionnaires, data analysis models followed by findings and discussions. Section 4.3 explains the research design of gender-based e-learning adoption, data collection, data analysis, and discussions. Section 4.4 describes various e-learning barriers, research design, data collection and data analysis, followed by findings and discussions. Section 4.5 describes the performance of a cloud-based e-learning system by deploying the CloudAnalyst simulator followed by results. Finally, chapter 4 is concluded in section 4.6.

4.2 Study 1 - Factors Influence E-learning Adoption

This study determines e-learning adoption factors in the Indian context. The target population of this study is higher education students. The conceptual model has been developed with the help of TAM and McLean models. In the study, these two models are combined to measure e-learning adoption. In previous empirical studies, the authors used these theories separately (DeLone & McLean, 2003). Through literature, the factors that influence e-learning adoption are identified and included in the conceptual model. The research model is shown in Figure. 4.2

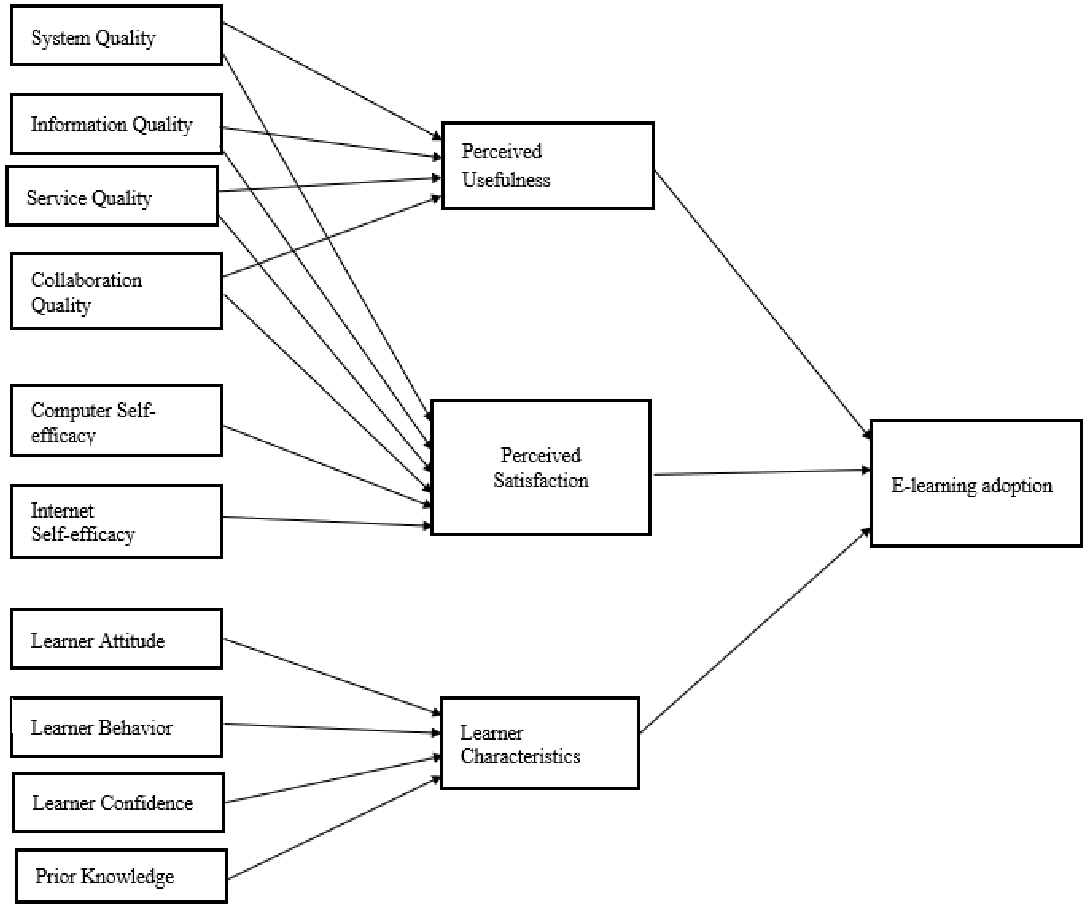


Figure 4.1: E-learning Adoption Research Model

Under the technological dimension, the independent variables identified are system quality, information quality, service quality, collaboration quality, computer self-efficacy and Internet self-efficiency. In the learner's dimension, the independent variables are the learner's attitude, behaviour, confidence, and prior knowledge (Aparicio et al., 2017; Urbach et al., 2010a, 2010b). The learner characteristics are influenced by all learner dimension constructs (learner attitude, learner confidence, learner behaviour and prior knowledge). All other constructs, perceived usefulness, perceived satisfaction, learner characteristics and e-learning adoption, are dependent variables.

4.2.1 Hypotheses

System quality factor is an external variable that measures the reliability and accessibility of the e-learning system (Davis, 1998; Delone & Mclean, 2014; Bailey & Pearson, 1983). The user's belief in using the system will help learners adopt e-learning systems (DeLone & McLean, 1992, 2014; Kim & Park, 2018). Hence, hypotheses H1a and H1b have been formulated concerning the SQ that influences PU and PS.

H1a: System quality will positively influence perceived usefulness in e-learning adoption.
H1b: System quality will positively influence perceived satisfaction in e-learning adoption.

The information quality also improves system utilisation. It will also increase user intention to use the e-learning system (Lee & Choi, 2010; Machado-Da-Silva et al., 2014; Lin & Lee, 2006; Lin & Lu, 2000 Urbach et al., 2010a, 2010b; DeLone & McLean, 2003. Also, accurate content and timely response improve user satisfaction (Lin & Lu, 2000; Lee & Quek, 2017). Hence, H2a and H2b have been formulated concerning information quality that influences perceived usefulness and perceived satisfaction, respectively.

H2a: Information quality will positively influence perceived usefulness in e-learning adoption.
H2b: Information quality will positively influence perceived satisfaction in e-learning adoption.

The e-learning service providers give reliable service' improves the service quality of the e-learning system. The gap between learner expectation and experience is measured to provide better service. Based on learners' feedback, improvements are made. Thus, it increases the learner adoption and perceived satisfaction towards e-learning. Hence, hypotheses H3a and H3b have been formulated concerning service quality that influence perceived usefulness and perceived satisfaction.

H3a: Service quality will positively influence perceived usefulness in e-learning adoption.
H3b: Service quality will positively influence perceived satisfaction in e-learning adoption.

The collaboration quality is considered a critical factor because many social constructivism models highlight the importance of collaboration in e-learning. Several studies confirm that CQ improves user intends to use the e-learning system (Nam & Zellner, 2011). Moreover, proper structure and cooperation among groups also improve perceived satisfaction (Paechter & Maier, 2010; Weiser et al., 2018). Hence, hypotheses H4a and H4b have been formulated concerning CQ that influence perceived use and perceived satisfaction, respectively.

H4a: Collaboration quality will positively influence perceived usefulness in e-learning adoption.
H4b: Collaboration quality will positively influence perceived satisfaction in e-learning adoption.

Computer self-efficacy and Internet self-efficacy have a strong relationship with learning theory. The learner awareness about online courses also improves perceived satisfaction (Parkes et al., 2015; Simmering et al., 2009). The learners' computer knowledge and skills are helpful to handle the online course effectively (Joo et al., 2000; Thompson et al., 2002). The users' ability to handle the Internet effectively will increase the intention to use the e-learning system (Joo et al., 2000; Parkes et al., 2015; Thompson et al., 2002). Internet self-efficacy is classified into two categories: general and specific purpose. In general, Internet self-efficacy, the learner's ability to handle the primary function, is measured (Elkaseh et al., 2016; McKinney et al., 2002; Wu & Tsai, 2006). Simultaneously, specific Internet self-efficacy analyses the learners' capacity to operate Internet functions and applications (Peng et al., 2006). In this study, the learners' Internet self-efficacy towards the e-learning system is explored. The previous study concluded that computer self-efficacy and Internet self-efficacy have a positive influence on PU and PS. Hence, hypotheses H5, H6has been formulated concerning CS and IS positive influence user satisfaction, respectively.

H5: Computer self-efficacy will positively influence perceived satisfaction in e-learning adoption.
H6: Internet self-efficacy will positively influence perceived satisfaction in e-learning adoption.

Based on social cognitive theory and constructivism theory, the constructs that influence learner characteristics are derived. Liaw (2008) concluded that learners' attitude affects learners' characteristics. The awareness about the e-learning course and computer resources increases the user's positive attitude (Barbeite & Weiss, 2004; Sun et al., 2008). Second, the learner's behaviour measures the online activity of participants. It indicates how an efficient learner handles Internet facilities and other digital resources (Gong et al., 2004; Shroff et al., 2011). The positive behaviour also increases the belief to adopt an e-learning system. Third, the confidence level denotes the usage of online resources and materials. The learners' confidence automatically encourages them to register for more online courses and make them complete successfully (Liaw, 2004). Apart from this, prior knowledge about the online system reduces the wastage of time and online resources.

Therefore, the learning characteristics are positively correlated with learner theories (Jan 2015; Pellas, 2014; Simmering et al., 2009). Thus, learner characteristics are positively influenced by the learner's attitude, behaviour, confidence, and prior knowledge. Therefore, the current research hypotheses H7, H8, H9 and H10 represent that the learner attitude, behaviour, confidence, and prior knowledge positively influence the e-learning platform's user characteristics.

H7: Learners' attitude will positively influence learners' characteristics in e-learning platforms.
H8: Learners' behaviour will positively influence learners' characteristics in e-learning platforms.
H9: Learners' confidence will positively influence learners' characteristics in e-learning platforms.
H10: Learners' prior knowledge will positively influence learners' characteristics in e-learning platforms.

This study measures the e-learning system adoption (EA) using PU, PS, and LCH. The learner believes that communication skill is improved after participating in the e-learning course. Compared to traditional learning, online education's quality and time will improve the learners' knowledge level (Moore et al., 2011). It makes the learner familiarise with the new technologies. The knowledge gained in the online course will also reflect in the academic activities of the learner. Therefore, the learner is willing to adopt e-learning (Mohamed, 2019; Liu & Feng, 2011). Liaw (2008) confirms that perceived usefulness and perceived satisfaction have a positive influence on e-learning adoption. Learner characteristics are considered one of the critical factors determining the success of e-learning (Ozkan et al., 2009; Selim, 2007).

H11: Perceived usefulness will positively influence e-learning adoption.

H12: Perceived satisfaction will positively influence e-learning adoption.

H13: Learners' characteristics will positively influence e-learning adoption.

Therefore, the three constructs are added to the research model. These constructs are positively correlated with e-learning adoption. Hypotheses H11, H12 and H13, represent perceived usefulness, perceived satisfaction and learner characteristics that influence the e-learning adoption. Thus, the three predictors' PU, PS and LHC, have been used to analyse e-learning adoption in the Indian context. Based on the literature support, the hypotheses are framed and tested using survey-based research methods.

4.2.2 Research methodology

The conceptual model is validated using quantitative methods. Questionnaires were developed in the English language. Based on the literature support, the questionnaire was developed and shown in Appendix A. The average time estimated to complete the survey is 10 min. The pre-test was conducted to validate the questionnaire. It's circulated among the PhD students to check the face validity of the questionnaire. Both online and offline questionnaires were distributed to graduate and undergraduate students in higher education institutions.

The survey hyperlink was sent to the coordinators of the various engineering colleges. Then, the co-coordinators are requested to forward the link to the students through social media like WhatsApp and Facebook. The objective of the study is explained clearly in the questionnaire. It is also mentioned that the personal information about the respondent was not enclosed anywhere. The tracking system is not involved in this study. Therefore, the student agrees to give their response to the survey.

Data was collected from 815 respondents from various Indian universities. Only 704 responses were complete, and other partial-filled questionnaires were not taken in the count. This study includes all higher education institutions like central government institutions, state government/institutions, private and public colleges. There is no personal information collected from respondents. The demographic information of the participant is shown in Table 4.1.

Table 4.1 Demographic details of the participants

Categories	Urban area	Frequency	Percentage
Gender	Male	498	70.7
	Female	206	29.2
Age	18–23	348	49.4
	23–30	300	42.6
	Above 30	56	8.0
Grade level	Bachelor degree	439	62.35
	Master degree	207	29.4
	Advanced graduate/PhD	58	8.25
Organisation detail	Central government institution	447	63.5
	State government institution	144	20.5
	Private institution	113	16.0
MOOC platform used	Coursera	602	85.8
	Edx	450	63.9
	Udacity	399	56.7
	Khan Academy	447	63.5
	Udemy	431	61.2
	Alison	499	70.9

4.2.3 Analysis and results

The collected data would be treated confidentially, and no monitoring system is involved. The data were collected from the period of November 2018 to April 2019. Seven hundred four responses are used in the analysis. The questionnaires consist of a five-level Likert item (SD = 1 to 5; strongly disagree to strongly agree) (Al-Fraihat et al., 2019; Johnson & Duberley, 2013). The demographic details of users, including gender, age, type of organisation and learner's familiar e-learning platform, is also included and shown in Appendix A.

The analysis is carried out through the PLS- structural equation model (PLS-SEM) method. It is used to measure the relationship between latent constructs in the research model. Hair et al. (2019) explains various thumb rules to choose the PLS-SEM model during data analysis. The PLS-SEM model is preferred in the current study for the following reasons. First, PLS-SEM is a predictive analysis technique utilised to evaluate a theoretical structure and encourage theory development. In other words, PLS-SEM is often used to analyse theoretical models built based on existing literature. In our research, we built a new theoretical model based on the IS and learning theories. As a result, PLS-SEM is used in the current study to measure the predictive relationship between the constructs and to maximise the amount of covariance. Second, PLS-SEM is preferred when the model is complex and consist of many constructs, indicators, and model relationships. Despite the structural model's complexity, PLS-SEM helps comprehend the research model (Sosik et al., 2009). The model proposed in the current study is a complex structural model consisting of constructs adopted from various theories to analyse the relationship between them and to enhance research model interpretation. Thus, this study utilised PLS-SEM as suggested by Hair et al. (2019) to test the hypotheses.

Many researchers suggest this method because of its flexible feature in data usage, model complications, and related description (Hair et al., 2012; Sarstedt et al., 2014). Compared to other approaches, advanced features are used in this method (Sarstedt et al., 2014). Many researchers suggested that PLS-SEM path modelling is suitable for business-based forecast problems, tourism, and hospitality research (Cidral et al., 2018; Huber et al., 2007; Ringle et al., 2012; Tarhini et al., 2014; Urbach & Ahlemann, 2010a). The result analysis is discussed under two sections: assessing the measurement model and assessing the structural model.

4.2.3.1 Assessment of the measurement models

The constructors are developed using reflective indicators. In this research, model indicators are caused by latent variables. The validity and reliability test were carried out to check the accuracy and reliability of the questionnaire. Using Fornell and Larcker (1981) criterion, the measurement model was analysed. The three criteria used are, first, the indicator reliability is tested through outer loading values. Second, Cronbach's alpha (CA) and Composite Reliability (CR) are carried to check the reliability. Third, the discriminant validity test was conducted to ensure that the constructs have strong relationships with their indicators. The strong relationship between each indicator's underlying factor is measured under outer loading. The purpose of this test is to identify the weak indicators' and remove them from the model (Hair et al., 2017; Hafez, 2018; Gong et al., 2018; Cidral et al., 2018; Urbach & Ahlemann, 2010b). In this study, the factor loading values range from 0.711 to 0.962. The total indicator score of constructs was above 0.70, and hence internal consistency was satisfied (Cidral et al., 2018; Peter, 1979).

The construct reliability and validity of the proposed model is measured using CA, CR and AVE values. To ensure reliability, the value of CA and CR has to be greater than 0.7. Even the value of 0.6 is also accepted for exploratory research (Urbach et al., 2010a, 2010b; Henseler, 2010). In this study, the CA values lies between 0.708 and 0.919, and the CR

Table 4.2 Construct reliability and validity test

Construct	Items	Factor loading	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
System quality	SQ1	0.865	0.848	0.908	0.766
	SQ2	0.891			
	SQ3	0.869			
Information quality	IQ1	0.896	0.887	0.930	0.816
	IQ2	0.925			
	IQ3	0.887			
Service quality	SE1	0.914	0.773	0.869	0.691
	SE2	0.855			
	SE3	0.711			
Collaboration quality	CQ1	0.717	0.700	0.832	0.625
	CQ2	0.739			
	CQ3	0.903			
Computer self-efficacy	CS1	0.872	0.826	0.896	0.742
	CS2	0.861			
	CS3	0.850			
Internet self-efficacy	IS1	0.937	0.884	0.930	0.815
	IS2	0.952			
	IS3	0.813			
Learner attitude	LA1	0.759	0.701	0.831	0.623
	LA2	0.732			
	LA3	0.870			
Learner behaviour	LB1	0.799	0.798	0.876	0.702
	LB2	0.819			
	LB3	0.893			
Learner confidence	LC1	0.922	0.919	0.949	0.861
	LC2	0.937			
	LC3	0.925			
Prior knowledge	PK1	0.962	0.813	0.895	0.746
	PK2	0.624			
	PK3	0.961			
Perceived usefulness	PU1	0.769	0.844	0.894	0.679
	PU2	0.791			
	PU3	0.864			
	PU4	0.868			
Perceived satisfaction	PS1	0.917	0.913	0.945	0.851
	PS2	0.933			
	PS4	0.917			
Learner characteristics	LCH1	0.839	0.837	0.902	0.755
	LCH2	0.876			
	LCH3	0.890			
E-learning adoption	EA1	0.885	0.869	0.919	0.792
	EA2	0.907			
	EA3	0.878			

values lie between 0.831 and 0.949). The estimated loading values, the construct validity and reliability results are shown in Table 4.2

Thus, the CA and CR values were satisfactory, and construct reliability was confirmed. According to Fornell and Larcker (1981), the AVE test is conducted as a part of convergent validity. The constructs with a value above 0.50 are accepted, confirming that the constructs have adequate validity (Segers, 1997

The discriminant validity identifies the relationship between the reflective constructs in the model. It checks that any two constructs in the model are not related to each other. The AVE square root values should be higher than correlations between any pair of constructs in the model to ensure discriminant validity. The result obtained in the study meets the discriminant validity. It confirms that all constructs are distinctive in the model. The AVE square root is highlighted in bold in the inter construct of a correlation table shown in Table 4.3. The result shows that all the latent variables are distinctive in the model.

Table 4.3 Discriminant Validity: Fornell-Larcker Criterion

	EA	IS	CQ	CS	IQ	LA	LB	LCH	LC	PS	PU	PK	SE	SQ
EA	**0.890**													
IS	0.609	**0.903**												
CQ	0.733	0.723	**0.790**											
CS	0.585	0.729	0.806	**0.861**										
IQ	0.528	0.467	0.599	0.418	**0.903**									
LA	0.736	0.619	0.733	0.583	0.680	**0.789**								
LB	0.674	0.740	0.846	0.631	0.603	0.683	**0.838**							
LCH	0.783	0.638	0.695	0.554	0.580	0.855	0.641	**0.869**						
LC	0.728	0.724	0.844	0.723	0.693	0.824	0.771	0.739	**0.928**					
PS	0.728	0.719	0.802	0.692	0.676	0.792	0.741	0.747	0.945	**0.923**				
PU	0.623	0.709	0.743	0.564	0.509	0.615	0.889	0.608	0.685	0.681	**0.824**			
PK	0.607	0.525	0.581	0.440	0.549	0.859	0.513	0.800	0.666	0.662	0.465	**0.864**		
SE	0.726	0.625	0.774	0.642	0.713	0.742	0.732	0.695	0.834	0.817	0.658	0.545	**0.831**	
SQ	0.659	0.482	0.694	0.508	0.827	0.731	0.604	0.665	0.753	0.716	0.521	0.565	0.800	**0.875**

4.2.3.2 Assessment of the structural model

In the structure model, the relationship between the constructs is tested using hypotheses. The factors that improve e-learning adoption was analysed in this study. Based on multiple square correlations (R^2), the quality of the structural model was measured. In

PLS-SEM, 704 samples were run to find the structural model's path value. The model explains R^2= 0.583 (58.3%) of variations in PU; R^2 = 0.777 (77.7%) of variations in PS, R^2 = 0.760 (76.0%) of variations in LCH and R^2 = 0.670 (67.0%) of variations in EA. Overall, the model explains 66.8% of the variance in EA; therefore, all the constructs are acceptable for this model.

The relations between explanatory and predicted variables are measured using path analysis. The hypothesis was tested with the corresponding path coefficient values. The significant value for p should be less than 0.05. The result obtained through the path coefficient is shown in Fig. 4.2. In this study, 17 hypotheses were framed to verify the conceptual model. 12 hypotheses were strongly significant at p = 0.000, 2 hypotheses are significant at p < 0.010 and 3 hypotheses were not significant, whose p-value is above 0.05. The result of hypothesis testing is illustrated in Table 4.4.

Table 4.4: Path coefficient values

	Hypothesis	beta-value	t-value	f2 value	p-value	Support	Effect
H1a	System quality → Perceived Usefulness	0.251***	5.132	0.033	0.000	Yes	Medium
H1b	System Quality → Perceived Satisfaction	**0.035**	**0.889**	**0.001**	**0.374**	No	Not supported
H2a	Information Quality→ Perceived Usefulness	0.153**	3.309	**0.017**	0.001	Yes	small
H2b	Information Quality → Perceived Satisfaction	0.145**	3.309	0.028	0.001	Yes	small
H3a	Service Quality → Perceived Usefulness	0.276***	5.802	0.048	0.000	Yes	large
H3b	Service Quality→ Perceived Satisfaction	0.338***	11.293	0.128	0.000	Yes	small
H4a	Collaboration Quality → Perceived Usefulness	0.611***	15.423	**0.345**	0.000	Yes	medium
H4b	Collaboration Quality → Perceived Satisfaction	0.226***	5.282	0.048	0.000	Yes	small
H5	Computer Self-efficacy→ Perceived Satisfaction	**0.054**	**1.605**	**0.004**	**0.109**	No	Not supported
H6	Internet Self-efficacy→ Perceived Satisfaction	0.22***	4.580	0.086	0.000	Yes	small
H7	Learner Attitude → Learner Characteristics	0.462***	6.623	0.127	0.000	Yes	small
H8	Learner Behavior → Learner Characteristics	0.123***	4.417	0.024	0.000	Yes	small
H9	Learner Confidence → Learner Characteristics	**0.066**	**1.900**	**0.004**	**0.058**	No	Not supported
H10	Prior Knowledge → Learner Characteristics	0.297***	5.032	0.092	0.000	Yes	small
H11	Perceived Usefulness→ E-learning Adoption	0.143***	4.460	0.032	0.000	Yes	small
H12	Perceived Satisfaction → E-learning Adoption	0.250***	6.135	0.068	0.000	Yes	small
H13	Learner Characteristics → E-learning Adoption	0.509***	14.902	**0.332**	0.000	Yes	medium

Notes: significant at **p* < 0.05; ***p* < 0.01; ****p* < 0.001

Source: Hair et al. (2019).

Hypothesis H1a shows that the SQ was positively significant to (beta value = 0.251***; p < 0.01) PU. Hypothesis H2a shows that the SQ was not significant to (beta value = 0.35***; p = 0.34) PS. Hypothesis H2a, H3b shows that the IQ was positively significant to (beta value = 0.153***; p < 0.01; beta value = 0.145***; p < 0.01) PU and PS. Hypothesis H3a, H3b, shows that the SE was positively significant to (beta value = 0.276***; p = 0.00;beta value = 0.338***; p = 0.00)PU and PS. Hypothesis H4a, H4b, shows that the CQ was positively significant to (beta value = 0.611***; p = 0.00; beta value = 0.226***; p = 0.00) PU and PS. Hypothesis H5 shows that the CS was positively significant to (beta value = 0.054***; p = 0.109) PS. Hypothesis H6 shows that the IS was positively significant to (beta value = 0.22***; p = 0.00) PS.

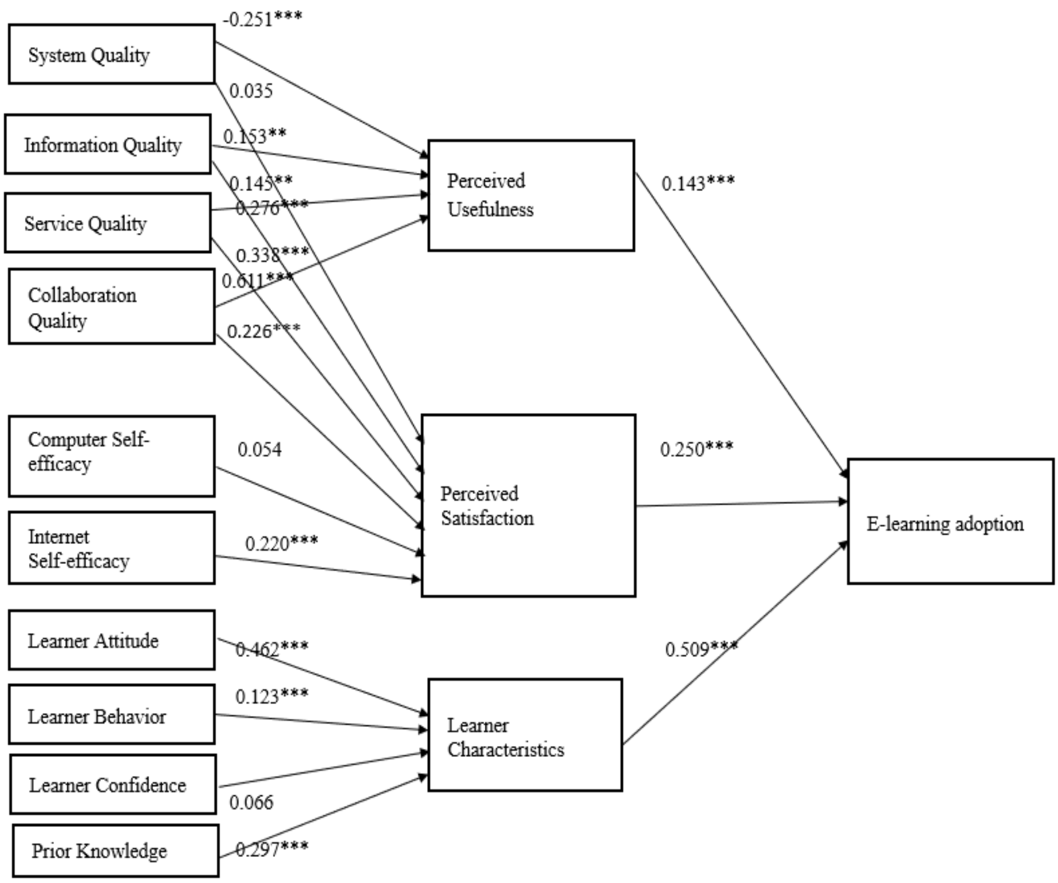


Figure 4.2: Path coefficient of the proposed model

Hypothesis H7 shows that the LA significantly and positively influence LCH (beta value = 0.462***; p = 0.000). Hypothesis H8 indicates that the LB significantly and positively influence LCH (beta value = 0.123***; p = 0.00). Hypothesis H9 shows that the LC does not significantly influence LCH (beta value = 0.066; p = 0.058). Hypothesis H10 shows that the PK significantly and positively influence LCH (beta value = 0.297***; p =

0.00). Hypothesis H11 shows that the PU significantly and positively influence EA (beta value = 0.143***; p = 0.00). Hypothesis H12 shows that the PU significantly and positively influence EA (beta value = 0.250***; p = 0.00). Hypothesis H13 shows that the LCH significantly and positively influence EA (beta value = 0.509***; p = 0.00). Hence all the hypotheses are verified, and the proposed model was validated.

4.2.4 Discussion

The perceived usefulness is determined by SQ, IQ, SE and CQ, and the perceived satisfaction is predicted by SQ, IQ, SE, CQ, CS, and IS. Similarly, learner characteristics are determined by LA, LB, LC and PK. Finally, e-learning adoption is determined by perceived usefulness, perceived satisfaction and learner characteristic. The hypothesis test confirms that PU and PS will improve e-learning adoption. Meanwhile, LHC also increased the chance to adopt more students towards e-learning. The constructs SQ, IQ, SE and CQ would improve learners' belief and performance through PU. Hence PU of the system influences learners to adopt e-learning. The path from the hypotheses H1a, H2a, H3a, H4a, and H11 are significant, which implies that the quality factor of the e-learning system creates positive belief among users to adopt e-learning. The path from H2b, H3b, H4b, H6 and H12 are significant because learners are satisfied with the IQ, SE and CQ of the e-learning system. Thus, it automatically increases the learners to adopt the e-learning system.

Meanwhile, SQ and CS are not satisfied with PS. Lack of system quality and efficacy would decrease the learner satisfaction level. On the other hand, a lack of computer self-efficacy would reduce the learner satisfaction level. The path diagram shows that SQ and CS are not significant towards PU, which affects e-learning adoption. Our finding indicates that LA, LB, and PK to LCH are significant, which influence LCH. The path from H7, H8 and H10 are significant, whereas LC (H9) is insignificant to LCH. This is due to a lack of individual influence, social collaboration and perception about e-learning.

The system quality significantly influences perceived usefulness (H1a). The previous studies also found the same result in e-learning studies and employee portals. Even though system quality is associated with perceived usefulness, it is not positively related to perceived satisfaction. (H1b). Authors report the same result in e-learning success. It shows that the learners are not satisfied with the system quality in the e-learning platform. But the contrary result is reported by the authors in e-learning success studies (Cidral et al., 2018). The information quality significantly influences both perceived usefulness and perceived satisfaction (H2a and H2b). The content quality and course objective would increase the learner's interest to adopt an e-learning system. The same result was found in the previous studies related to e-learning success (Aparicio et al., 2017; Machado-Da-Silva et al., 2014). The service quality significantly influences both perceived usefulness and perceived satisfaction (H3a and H3b). This finding is consistent with the results found by the authors (Cidral et al., 2018). At the same time, other studies reported that service quality has no significant effect on use and user satisfaction (Urbach et al., 2010a, 2010b). Therefore, service quality is considered one of the critical factors in e-learning adoption.

The service quality significantly influences both perceived usefulness and perceived satisfaction (H3a and H3b). This finding is consistent with the results found by the authors (Cidral et al., 2018). In contrast, other studies reported that service quality has no significant effect on use and user satisfaction (Urbach et al., 2010a, 2010b). In this study, collaboration quality significantly influences perceived usefulness and perceived satisfaction (H4a and H4b). The change made in the e-learning forum or online environment will attract many learners towards e-learning adoption. Our study's findings are similar to the previous results found in e-learning usage and individual impact (Wang, 2003; Cidral et al., 2018).

Computer self-efficacy has no significant impact on perceived satisfaction (H5). The finding is similar to the previous results related to e-learning use (Pituch & Lee, 2006). The result found in the study is contradictory to the previous study. Liaw (2008) reported that self-efficacy was identified as a predictor of perceived satisfaction. The previous studies also reported that computer self-efficacy significantly relates to satisfaction in e-learning studies (Ifinedo, 2017). Internet self-efficacy significantly influences perceived satisfaction (H6). The learners' interest to use the Internet would improve e-learning adoption. The previous studies found that Internet self-efficacy is interlinked with perceived satisfaction in e-learning readiness (Kuo et al., 2014). Our result is consistent with other studies. The result shows that the learners' Internet self-efficacy would motivate and increase perceived satisfaction (Huang, 2002; Offir et al., 2004; Yilmaz, 2017).

The learner attitude significantly influences learner characteristics (H7). The previous studies identified learner attitude as one of the critical factors in learner characteristics (Passerini & Granger, 2000). The learner's positive attitude towards technology would improve e-learning effectiveness (Yudko et al., 2008; Ahmed, 2010). Our result is similar to previous studies. Learner characteristics such as attitude, self-paced learning, and interest affect e-learning adoption (Liaw et al., 2007b; Oliver & Omari, 2001; Sun et al., 2008). Hence learner attitude is considered as one of the critical factors in learner characteristics. Learner behaviour significantly influences learner characteristics (H8). The previous studies confirm learner behaviour as a critical factor in learner characteristics. The individual behaviour of the learner would determine e-learning adoption. The previous studies also reported a positive attitude and behaviour significantly related to e-learning (Liaw et al., 2007a, 2007b). Our finding is consistent with the previous studies.

Learner confidence has no significance with learner characteristics(H9). The previous studies confirm that e-learning is considered a suitable platform to improve the learner's confidence level. And it is the learners' responsibility to build self-confidence in the e-learning environment (Nneka Eke, 2010). Our finding confirms that some limitations will decrease the learner's confidence to adopt e-learning. Lack of self-confidence, lack of skills and learners' perception towards e-learning is the main factor that reduces e-learning adoption (McLester, 2002). Park and Wentling (2007) suggest the e-learning experience or prior knowledge about the e-learning system would increase the learner's confidence.

Prior knowledge significantly influences learner characteristics(H10). The previous studies also confirm that prior knowledge would help learn efficiently in the online environment (Ahmed, 2010; Jeong Kim et al., 2012; Oliver & Omari, 2001). Our findings also support the same result. The online course and social media platform's prior knowledge would help learners complete the course successfully. Perceived usefulness significantly influences e-learning adoption(H11). The learner believes that the adoption of e-learning systems would improve their performance. The quality of content with audio, video and multimedia support would attract the learners to adopt e-learning. Our study's result is correlated with the previous studies in the e-learning context (Ong et al., 2004; Venkatesh & Davis, 1996; Venkatesh, 1999). Perceived satisfaction significantly influences e-learning adoption(H12). Learner satisfaction depends upon the tools and e-learning platform (Fleming et al., 2017). The previous studies also support the same result. Our findings also support the same result.

Learner characteristics significantly influence e-learning adoption(H13). The learner characteristics, including learner attitude, learner behaviour, and prior knowledge, positively influence learner characteristics. The previous studies also support the same results (Ahmed, 2010; Liaw et al., 2007a, 2007b; Selim, 2007; Sun et al., 2008; Susskind, 2005). Our findings mention that computer self-efficacy mainly focuses on the learner confidence towards e-learning adoption. The previous studies also concluded that computer self-efficacy has a significant relation with confidence. This study also confirms a correlation between computer self-efficacy and learner confidence (Park & Wentling, 2007). Our finding also supports the same result. From the above result, it is confirmed that the learner would adapt to a user-friendly e-learning platform. In our findings, the learners are not satisfied with the system quality; thus, it reduces their confidence level in the e-learning platform. Another reason identified in this study is the lack of computer self-efficacy, which reduces the learner's confidence.

4.3 Study 2 - Gender-based E-learning Adoption

This study analyses the various e-learning factors that influence e-learning adoption based on gender differences. The research model integrates individual performance and social behaviour of the users. The attributes are identified through literature support and interlinked using learning theories based on gender. The research model is designed based on the attributes and shown in Figure 4.3.

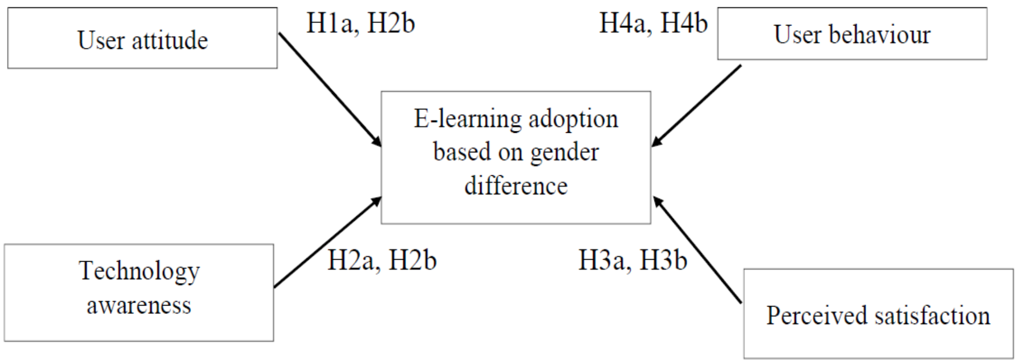


Figure 4.3: Research Model

The research model contains four theoretical constructs related to gender-based e-learning adoption: user attitude (UA), technology awareness (TA), and perceived satisfaction (PS), user behaviour (UB). The factors identified in the UA are belief, need usefulness, fun, and performance, confidence and user anxiety (Szymanski & Hise, 2000; Jaiyeoba & Iloanya, 2019). The TA includes computer skills, familiarity with e-learning technologies, prior knowledge about the online course, and internet usage as sub-factors (Folorunso et al., 2006). The attributes that determine the PS are accessibility and flexibility service, sufficient e-learning content, internet availability, self-efficiency, technology efficiency, and convenience (Conrad & Munro, 2008; Sun et al., 2008). UB includes the following sub-index communication and collaborative environment, confidence to share ideas in the e-learning platform, and reflex improvement in the learning process to construct the factor (David et al., 2007). Based on these four factors, the hypotheses are formed.

User attitude

When the user feels the needs are met, it automatically creates a positive attitude among users. The positive attitude of the user towards a collaborative environment will improve e-learning adoption. It also increases the ease of use and usefulness of the e-learning system. Even though the course platform is well structured, it does not meet users' needs. Thus, it decreases the fun, performance, and confidence level of the user. Meanwhile, this negative attitude increases user anxiety towards the e-learning system (Smith et al., 2000; Bishop, 2007). Overall, the user attitude is considered as one of the crucial factors to determine gender-based e-learning adoption. According to Lu and Chiou (2010), gender is also considered as one of the factors to adopt e-learning services. Previous studies confirmed that male users have a positive attitude towards e-learning (Abidin et al.,2018). According to Marriott and Marriott (2003), male students in Malaysia have a more positive attitude than female students. Barkatsas et al. (2009) confirm that male students have more belief and confidence in technology-based learning. Therefore, the hypothesis formed as,

$H1_{a,b}$: The association between attitude and e-learning adoption will be positive and more stronger for males than females.

Technology awareness

The users' technology awareness or familiarity with various e-learning tools is measured in this study. Previous studies also concluded that individuals' prior knowledge about e-learning has a positive effect on their attitude towards e-learning (Mick & Fournier, 1998). Computer skills, prior training, and efficient internet usage automatically increase technology awareness among users. The familiarity with the e-learning tools and prior knowledge about online courses also increase awareness levels. Technological awareness increases user adoption of e-learning. Internet skills and prior experience are observed as important factors among Indian users (Swamy, 2010). Thus, ICTs skills and internet usage create a gender gap in e-learning adoption. The previous studies also conclude that there is a gender gap exists due to technology awareness. Male users, compared to females, are more familiar with the Internet and e-learning environments. Females use internet facilities for purposes other than academic research, according to Ahmad et al. (2018). Purushothaman (2013) also stated that a lack of internet skills is the primary cause of females' lack of technology awareness. However, Thakur (2014) reported a lack of ICT awareness among male and female users in the Indian context. Therefore, the hypothesis is framed as:

H2$_{a,b}$: The association between technology awareness and e-learning adoption will be positive and more stronger for females than males.

Perceived satisfaction

The users' confidence to use ICTs and the Internet is termed as technology efficiency. The availability of the e-learning service will improve user satisfaction. Sufficient content availability and adequate internet facility are also considered as critical factors. The online course delivery according to the learner style and convenience also increases satisfaction level. The motivation and confidence level of users determines the adoption of e-learning. Piccoli et al. (2001) conclude that the e-learners have more technical knowledge than traditional classroom learners. It automatically improves the satisfaction level of the users. Perceived satisfaction is regarded as one of the most important factors in determining e-learning adoption in this study (Eom et al., 2016). Even though the online course is the same, the opinion of the users is varied based on gender. The perceived satisfaction level of the users to adopt e-learning services is measured based on gender differences. According to Shen et al. (2013), gender significantly predicts user self-efficacy, which in turn influences perceived satisfaction. Li (2019), on the other hand, argued that gender does not predict perceived satisfaction. Previous research suggested that female users have higher perceived satisfaction than male users. This is because female users value the e-learning course more than male users (Young & Norgard, 2006). According to Shea et al. (2005), females understand the online community more than male users. Guiller and Durndell (2007) discovered that females are more responsible and explicitly agree with other people's points of view in a collaborative setting. So, the hypothesis is constructed as,

H3$_{a,b}$: The association between perceived satisfaction and e-learning adoption will be positive and more stronger for females than males.

User behaviour

The communicative and collaborative behaviour of the user increases e-learning adoption. It also improves the confidence level of the user and the same reflex in the learning process. As per the self-efficiency theory, the individual will adapt to the learning environment based on behavioural strategies (Sawang et al., 2013; Pedersen, 2005). Furthermore, user behaviour improves their technical skills and learning experience. In addition, prior knowledge about the online course increases the users' interest and reduces the dropout ratio (Li, 2018). Kay (2012) found that individual differences and self-efficiency influence user behaviour in the online environment. Thus, the gender based difference to adopt e-learning is analysed. Previous research suggested that female users react differently than male users. According to Chai and Hong (2009), female users contribute significantly less to project work than male users. Even though both genders have the same experience and attitude, male users are more active and seek out more knowledge than females. Despite having the same perception and academic experience, Forgasz et al. (2014) discovered that the male user performed well on the e-learning platform. Therefore, the hypothesis is framed as,

H4$_{a,b}$: The association between behaviour and e-learning adoption will be positive and more stronger for males than females.

Hence, all the hypotheses are framed based on the literature support. The two different measurement factors, including individual performance and social behaviour, are analysed based on gender.

4.3.1 Research methodology

Survey

The research model is validated using the quantitative method. The descriptive survey design was also carried out in this study. The results obtained from the samples are generalised for the total population. The justification for choosing the quantitative method is to provide conclusive evidence for gender-based e-learning adoption in the Indian context. The aim of using the descriptive approach is to explore individual performance in the e-learning platform. With the help of literature support, the questionnaire is framed, and hypotheses are developed. The purpose of these hypotheses is to answer the research question designed in the study. The questionnaire consists of two parts: demographic data and e-learning adoption attributes.

The items to measure user attitude was adapted from Sun et al. (2008), Piccoli et al. (2001), Arbaugh (2000, 2002), user behaviour from David et al. (2007), Sawang et al. (2013), Pedersen (2005), and for perceived satisfaction was adapted from Liaw (2008), Liaw and Huang (2013), Ngai et al. (2007), Wang (2003), Aixia and Wang (2011). The measures for technology awareness were adapted from Bishop (2007), Jaiyeoba and Iloanya (2019), Folorunso et al. (2006), and for e-learning adoption was adapted from George et al. (2014); DeLone and McLean (2003); Urbach et al., (2010).

The respondents were asked to answer the questionnaire using the Linker scale ranging from (1 to 5) where 1 = strongly disagree, 2 = agree, 3 = neutral, 4 = agree, and 5 = strongly agree. "The total population enrolled for higher education in India is 345,38,781. Out of this, 185,94,723 males and 159,90,058 females were enrolled" (Aishe.nic.in, 2019). This study adopts the purposive sampling technique. Even though purposive sampling is used more in qualitative research, it can be applied to quantitative research (Tongco, 2007).

Many researchers suggested purposive sampling in various fields, including e-learning adoption (Neupane et al., 2002). Mainly, this sampling technique is adopted in quantitative research in some special situations. It is used when the researchers need some selected cases with a specific purpose in their mind (van Manen, 2014; Campbell, 1995). The main purpose of this study is to focus on users who are familiar with the online course. Therefore, a purposive sampling technic is considered for this study (Anasi & Ali, 2014; Loh et al., 2016; Mahon & Niklas, 2016). The users who have attended at least one online course within a year's time period were chosen to participate in the survey. The sample population consisted of five engineering colleges. Two central governments, two state governments, and one private institution were chosen for this study. The students enrolled in the online courses are identified, and responses were collected. The sample size is determined with respect to the total number of students enrolled in higher education. The sample size of the current study is 385 with a 95% confidence level (Pan et al., 2010). A questionnaire was distributed among 450 students from various institutions in South India. Out of 450 respondents, 25 questionnaires were half-filled and excluded from the study. As a result, only 425 responses were considered for the analysis.

Data collection strategy

The questionnaire was developed in English, based on the literature support as shown in the Appendix A. The average time to complete the questionnaire is less than 15 minutes. The questionnaire was circulated among PhD students to check the clarity of the questions. The sampling strategy adopted in this study is, the institutions in south India are chosen. The hyperlink of the survey is sent to the coordinator through e-mail. The objective of the study is explained clearly in the questionnaire. The online and offline questionnaire survey was distributed among higher education students.

Moreover, it was explicitly pointed out that the respondent's personal information will not be revealed anywhere. Therefore, the respondent agrees to participate in the survey. The coordinator is asked to distribute the online survey form to the students. The survey is conducted between January 2019 to April 2019. The survey is balanced in terms of gender:

50% male and 50% female respondents were involved. All the respondents are above 18 years old.

Descriptive statistics result

The current study collected 425 participants responses (n = 219 male; n = 206 female) through the online and offline survey. Participants were aged between 18 to 22 (male = 163; female = 121), 23 to 26 (male = 37; female = 61), 26 to 30 (male = 19; female = 24). The grade level of the participants are bachelor degree (male = 149; female = 135), master degree (male = 48; female = 50), and advanced graduate PhD (male = 22; female = 21). The descriptive statistics of the sample are shown in Table 4.5.

Table 4.5 Descriptive statistics of the sample

Categories	Urban Area	Frequency		Percentage	
		Male (n=219)	Female (n=206)	Male (n=219)	Female (n=206)
Gender	Total	219	206	51.53	48.47
Age	18-22	163	121	74.43	58.74
	23-25	37	61	16.89	29.61
	26-30	19	24	8.68	11.65
	Total	219	206	-	-
Grade level	Bachelor degree	149	135	68.04	65.53
	Master degree	48	50	21.92	24.27
	Advanced Graduate/Ph.D.	22	21	10.05	10.19
	Total	219	206	-	-
Organization Detail	Central Government	109	87	49.77	42.23
	State Government	65	79	29.68	38.35
	Private Institution	45	40	20.55	19.42
	Total	219	206	-	-
MOOC platform used	Coursera	197	154	89.95	74.76
	Edx	112	98	51.14	47.57
	Udacity	92	106	42.01	51.46
	Khan Academy	56	61	25.57	29.61
	Udemy	102	86	46.58	41.75
	Alison	121	73	55.25	35.44
	NPTEL	186	113	84.93	54.85

Total Sample Size n=425

The participants were from different organisation like central government (male = 109; female = 87), start government (male = 65; female = 79), and private institution (male = 45; female = 40). The participants familiarities of the online courses are Coursera (male = 197; female = 154), Edx (male = 112; female = 98), Udacity (male = 92; female= 106), Khan Academy (male = 56; female = 61), Udemy (male = 102; female = 86), Alison (male = 121; female = 73), and NPTEL (male = 186; female = 113).

The cognitive constructivism of the respondents are user attitude (mean = 4.063 male; mean = 4.162 female), technology awareness (mean = 4.214 male; mean = 3.753 female), and perceived satisfaction (mean = 4.048 male; mean = 3.665 female). The social constructivism of the respondents is user behaviour (mean = 3.386 male; mean = 4.341

female). The mean and standard deviation values for e-learning adoption based on gender differences are shown in Table 4.6.

The descriptive statics of the variables used in the study is represented in tables. This result shows that the male students under the age of 18–22 in the bachelor's degree are active compared to the female students. In addition, the students from the central government institution actively participate in the survey response compare to the state government and other private institutions. Overall, the MOOC platform "Coursera" is preferred by many students, followed by NPTEL.

Table 4.6: E-learning adoption based on gender difference

E-learning adoption constructs	**Male (n=219)**		**Female (n=206)**	
	Mean	Standard deviation	Mean	Standard deviation
User attitude	4.063	1.022	4.162	0.903
Technology awareness	4.214	0.960	3.753	1.053
Perceived satisfaction	4.048	1.022	3.665	0.937
User behavior	3.386	1.083	4.341	0.814

4.3.2 Result analysis

The structural equation model (SEM) is adopted for the data analysis. The Partial Least Square (PLS) approach is used to evaluate the measurement properties and test hypotheses (Chin, 1998; Ringle et al., 2012). This study utilises the component-based estimation approach as suggested by previous researchers due to its flexibility feature (Hair et al., 2019, 2014). It is also easy to construct this model without any complexity (Tarhini et al., 2017). Future PLS-SEM is suitable to address the management problem and focus on the forecast. In this study, the data analysis is carried out into two steps:

- Measurement model evaluation
- Assessment of the structural model

In Step 1, the construct reliability and validity are measured along with factor loading. In Step 2, the path coefficient is calculated and hypotheses are validated (Hair et al., 2014; Tarhini et al., 2017).

Measurement model evaluation

The construct was developed using reflective indicators. The standard decision rule is applied to test the internal consistency, reliability and discriminant validity. The validation guidelines developed by Lewis et al. (2005) was followed. Ringle et al. (2012) were considered to do this analysis. Cronbach's alpha (CA) is conducted to test the internal consistency. The cut-off value for the CA is above .70. In our model, all the constructs have a value above 0.70, and hence the internal consistency was satisfied (Cronbach, 1951).

To overcome some limitations of CA, the composite reliability (CR) was calculated. The cut-off value for the CR is above 0.70 (Henseler, 2010). Therefore, the CR test is also carried out to test the accuracy of the model. In this study, the CR values were above the cut-off value, and hence the values were satisfied. The indicator reliability test is carried out to check the factor loading value. The cut-off value is above 0.40. In our model, the relation between each variable is above the cut-off value. The main purpose of doing this reliability test is to identify the week entity in the model. In this study, all the variables are above the significant range. Therefore, all the variables are included in this model. The result of the measurement model evaluation is shown in Table 4.7.

Table 4.7 Measurement Model Analysis: Factor loading values

Latent variable	Code	Male				Female			
		Loading values	CA	CR	AVE	Loading values	CA	CR	AVE
User attitude	UA1	0.926	0.938	0.955	0.843	0.926	0.915	0.940	0.798
	UA2	0.940				0.954			
	UA3	0.891				0.891			
	UA4	0.913				0.794			
Technology awareness	TA1	0.909	0.942	0.958	0.852	0.675	0.865	0.911	0.721
	TA2	0.915				0.877			
	TA3	0.950				0.927			
	TA4	0.917				0.896			
Perceived satisfaction	PS1	0.734	0.890	0.914	0.681	0.820	0.739	0.841	0.579
	PS2	0.792				0.868			
	PS3	0.881				0.838			
	PS4	0.881				0.873			
	PS5	0.829				0.739			
User behavior	UB1	0.909	0.917	0.942	0.804	0.877	0.901	0.931	0.771
	UB2	0.910				0.891			
	UB3	0.951				0.854			
	UB4	0.810				0.889			

The construct validity is measured using convergence validity along with discriminant validity. The correlation coefficient estimates convergence validity. According to Fornell and Larcker (1981), the cut-off value for the AVE is above 0.50. The discriminant validity result is shown in Table 4.8.

Table 4.8: Discriminant Validity measured in this study

	Constructs	PS	TA	UA	UB	Discriminant Validity
Male	PS	0.825				Supported
	TA	0.710	0.923			Supported
	UA	0.706	0.922	0.918		Supported
	UB	0.497	0.817	0.805	0.896	Supported
Female	PS	0.761				Supported
	TA	0.794	0.849			Supported
	UA	0.854	0.634	0.893		Supported
	UB	0.804	0.773	0.793	0.878	Supported

In our model, all values are above the cut-off value, and hence the result is satisfied (Urbach & Ahlemann, 2010). The discriminant validity measures the difference of each construct used in the model. The cut-off value of the discriminant validity is above 0.70. In our model, the values are above the threshold level and satisfied. The multi-collinearity is performed to test the variance inflation factors. The result shows that the collinearity statistics (VIF) lies between 1.032 to 7.154 for females and 1.250 to 6.127 for males. In general, the cut-off value of VIF less than 10 is acceptable (Hair et al., 1995; Alathur et al., 2016). Our result shows that the VIF values are less than 10 for both male and female users. Therefore, all the variables in the model are acceptable.

Assessment of the structural model

The relationship between the construct can be estimated by assessing the structural model. 5000 bootstraps resample were used to identify the structural model. The variation of the construct is explained in the structural model. The model explains 85% of e-learning adoption for males and 79% e-learning adoption for females. The overall result concludes that the e-learning adoption of the male is more than the female in the Indian context. The latent variables user attitude ($\beta = 0.438$***, $p < 0.000$) for male and ($\beta = 0.104$, $p < 0.187$) for female. Hence, hypothesis $H1_a$ regarding the association of attitude with e-learning adoption for male is positive and significant, whereas hypothesis $H1_b$ for female is positive and insignificant. It denotes that user attitude has a positive influence on e-learning adoption. The belief and confidence level of male users is more compared to female users. Due to various reasons, female users are anxious to use the e-learning system. Thus, the negative attitude of the female users decreases the interest to adopt e-learning systems. Hence, the hypotheses, H1a and H1b, were tested. The hypothesis $H1_{a,b}$ regarding stronger positive association between attitude and e-learning adoption for males than females was confirmed. Technology awareness (β = 0.013, $p < 0.891$) for male and (β = 0.236, $p < 0.060$) for female. The hypotheses $H2_a$ and $H2_b$ regarding the association of Technology awareness with e-learning adoption for male and female, respectively, were both positive and not significant. It indicates that technology awareness has a positive influence on e-learning adoption. But it is identified that the technology awareness of both genders is low in the Indian context. It implies that users need more awareness to handle online resources. Hence, the hypotheses H2a and H2b are tested. Though not statistically significant, the results denoted that the positive association between technology awareness and e-learning adoption were stronger for female than male. The path coefficient values are shown in Table 4.9.

Table 4.9 Path coefficient values observed in the study

Gender	Latent Variables	β value	p-value	Findings	Support
Male	UA - > EA	0.438***	0.000	Positive & statistically significant	Yes
	TA - > EA	0.013	0.891	Positive & statistically insignificant	No
	PS - > EA	0.096**	0.044	Positive & statistically significant	Yes
	UB - > EA	0.453***	0.000	Positive & statistically significant	Yes
Female	UA - > EA	0.104	0.187	Positive & statistically insignificant	No
	TA - > EA	0.236	0.060	Positive & statistically insignificant	No
	PS - > EA	0.532***	0.000	Positive & statistically significant	Yes
	UB - > EA	0.084	0.349	Positive & statistically insignificant	No

For perceived satisfaction (β =0.096**, $p < 0.044$) for male and (β = 0.532***, $p < 0.00$) for female. The hypotheses $H3_a$ and $H3_b$ regarding the positive association of perceived satisfaction with e-learning adoption for male and female, respectively, were both positive and significant. It specifies that the perceived satisfaction of the user has a positive influence on e-learning adoption. The result shows that both male and female users are satisfied with the existing e-learning. Hence, hypotheses $H3_a$ and $H3_b$ are confirmed. Furthermore, the results confirm $H3_{a,b}$ regarding stronger positive association between perceived satisfaction and e-learning adoption for females than males. The results are represented in the research model and shown in Figure 4.4.

Finally, user behaviour has (β = 0.453***, $p < 0.000$) for males and (β = 0.084, $p < 0.349$) for females. The hypothesis $H4_a$ regarding the association of user behaviour with e-learning adoption for male is positive and significant, whereas hypothesis $H4_b$ for female is positive but not statistically significant.

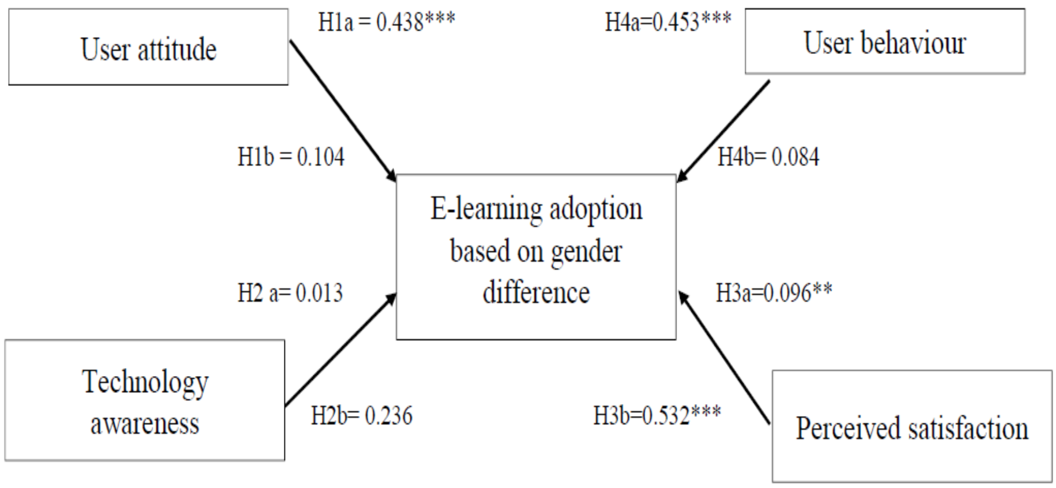


Figure 4.4: Path coefficient of the proposed model

The construct user behaviour has a positive influence on e-learning adoption. The communication and collaborative skills of male users are more compared to females. Hence the hypotheses $H4_a$ and $H4_b$ are tested. The hypothesis $H4_{a,b}$ regarding stronger positive association between behaviour and e-learning adoption was supported as males showed stronger positive association than female.

4.3.3 Discussions

Only limited studies have examined the factors associated with e-learning adoption based on gender differences. In that, only a few studies identified the influential factors for e-learning adoption and analysis of gender differences. However, previous studies do not analyse the gender difference against online courses like Coursera, Edx, NPTEL, etc. The main aim of this study is to identify e-learning adoption based on gender difference using the constructivism approach. The factors like user attitude, technology awareness, perceived satisfaction, and user behaviour is analysed. It identifies the factors according to the CLT. Gender is used as a control variable to analyse e-learning adoption in the Indian context. Based on four constructs, it has been analysed.

The result of the present study identified that there is significant difference between the two genders in e-learning adoption attributes. Specifically, this study concludes that male users are more interested in adopting e-learning than female users in India. The construct user attitude is significantly high compared to female users. The user behaviour in the online environment is more interactive for male users compared to female users. However, the constructs, namely technology awareness and perceived satisfaction, are equal for both genders. In India, limited technology awareness of users is considered as an important issue. This leads to a decrease in the use of e-learning and reduces the chances to adopt e-learning. Limited computer skills and prior knowledge are considered the main reasons. Finally, it is concluded that the perceived satisfaction of the male user is more due to a positive attitude and behaviour. Due to the lack of self-efficacy and technology efficacy, the satisfaction of female users is low.

The findings of our study are compared with previous studies and discussed as follows. First, the user attitude towards e-learning adoption is more for male users compared to female users. This is because male users have a positive belief, ease of use and more confidence level in the e-learning environment. This result is similar to previous studies. Abidin et al. (2018) reported that the user attitude towards computer usage is more positive for males. Barkatsas et al. (2009) also found that the male student has more belief and confidence level towards technology-based learning. Marriott and Marriott (2003) also reported that the male student attitude is more significant than female students in Malaysia. In contrast, Eng et al. (2016) reported that there is no significant gender difference in user attitude towards learning a mathematical course. However, the present study concludes that the attitude of the male users is positive, which increases the confidence level and performance. Thus, the male students easily adapt to the e-learning platform.

Second, technology awareness of the users for both gender is less in the Indian context. Although some studies have reported that male students have more technology awareness about ICTs than female students, our finding does not confirm this. This study identifies that both male and female users have limited technology awareness. The finding of this study supports the result of Verma and Dahiya (2016). This is because of the less prior knowledge about the online course (Bystrom, 2000; Mick & Fournier, 1998). Thus, the lack of technological awareness automatically decreases the e-learning adoption among users. In addition, internet skills and experience are also considered as important factors. The present finding, however, matched with the past studies done in the Indian context. Swamy (2010) found that users' internet skills as a critical factor in the e-learning platform. Similarly, Thakur (2014) also reported that there is a lack of ICTs awareness among male and female users in the Indian context.

In contrast, Ahmad et al. (2018) found that females use internet facilities other than academic activities. Compared to females, the male users have prior knowledge to handle the internet and e-learning environment. Purushothaman (2013) also reported that the lack of internet skill is the main reason for the lack of technology awareness in the female. In addition, Li and Kirkup (2007) conclude that male students spend more time on a computer than female students. Thus, the willingness and interest of the male student will increase the positive attitude towards the e-learning platform. However, our finding concludes that there is no significant difference in gender-based e-learning adoption in the Indian context. It explicitly implies that there is a lack of technological awareness among male and female users in the e-learning platform.

Third, the perceived satisfaction of males and females is discussed. Shen et al. (2013) found that gender significantly predicts user self-efficacy, which directly influences the perceived satisfaction. In contrast, Li (2019) argued that gender does not predict perceived satisfaction. However, perceived satisfaction is considered as one of the critical factors in this study to determine e-learning adoption (Eom et al., 2016). The previous findings suggested that perceived satisfaction is higher for female users than male users. This is because female users give more importance to the e-learning course than male users (Young & Norgard, 2006). In addition, female users are more interactive and satisfied with the quality of discussion. Shea et al. (2005) also reported that females have more sense in the online community than male users. Guiller and Durndell (2007) identified that females are more responsible and explicitly agree with other views in the collaborative environment. But the current study does not support the prior results. In contrast, our study revealed that both male and female users are satisfied with the e-learning environment.

In addition, past studies reported that the learning style of users is a predictor factor for perceived satisfaction. Mostly male users prefer assimilation style whereas female adopts accommodation style. As a result, the male student accepts other ideas but less prefer to interact with peers. However, female users like teamwork and are more interested in interacting and sharing ideas with peers. Due to this reason, the perceived satisfaction level is more in females than males. Overall, the current result also concludes that the perceived level of the female is more than male in the Indian context. This finding supports previous studies.

In contrast, some researchers argued that even though the female users have more goal settings, perceived satisfaction is lower than male users. This is because male users have more self-efficiency and experience compared to female users. Therefore, those researches conclude that male users have more perceived satisfaction than female users in the online environment (Kay, 2006; Shashaani & Khalili, 2001). Our finding does not match with the previous result as we found both genders are satisfied with the e-learning platform. Therefore, this research concluded that gender does not make any significant difference in perceived satisfaction during e-learning adoption.

Fourth, the construct user behaviour in the online environment is compared. The current research concludes that male users' behaviour in the e-learning platform is significantly higher than female users. This is because male users are more active participants in collaborative learning than female users. Chai and Hong (2009) reported that female users' contribution to the project work is significantly less than male users. Even though the experience and attitude are the same for both genders, it is found that male users are more active and explore more knowledge than females. These findings agree with those of previous research conducted by Roy et al. (2003). Even though the perception and academic experience are the same for both genders, Forgasz et al. (2014) found that the male user performed well in the e-learning platform. This finding remains constant with Barkatsas et al. (2009). Our result shows that male users have more positive behaviour in the e-learning platform.

In contrast, the previous studies suggested that female users' behaviour is more than male users. Prinsen et al. (2007) also reported that male users do not have social regulatory skills and lack involvement in the learning environment. On the other hand, female users are more agreeing and forward the conversion in learning. In addition, female users have more confidence in user computers compared to male users. Overall, this study concludes that male user behaviour is more positive in the online environment, which is considered as a positive sign to adopt e-learning.

4.4 Study 3- E-learning barriers that affect e-learning adoption

4.4.1 Research Model and Hypothesis

The present study analyzes the e-learning barrier in the Indian context. The proposed model integrates the technological barrier and individual barrier in the e-learning environment. The e-learning barrier factors were validated by literature support and a research model established with a strong foundation.

The conceptual model consists of 10 theoretical constructs as follows: ICTs facilities (ICTs), Internet facilities (IF), discomfort from the ICTs use (DICTs), technological barrier (TB), user anxiety (UA), lack of prior knowledge (LPK), lack of ICTs literacy (LICTs), individual barrier (IB), and barrier affects e-learning adoption (BEA). The main constructs of ICTs are lack of computer devices, inadequate e-learning platform, lack of software quality, and lack of interoperability (Acharya & Lee, 2018; Wiseman & Anderson, 2012; Mohammadi, 2015).

It includes low Internet speed, low accessibility, poor Internet quality, and improper Internet utilization (Mutisya & George, 2016). The DICTs consist of lack of infrastructure, lack of digital content, and insufficient bandwidth (Acharya & Lee, 2018; Mohammad et al., 2009). UA consists of lack of personal innovation, lack of Internet usage, and lack of technology awareness (Arai & Naganuma, 2010; Helbig et al., 2009; Shahid et al., 2015). The research model is shown in Figure. 4.5.

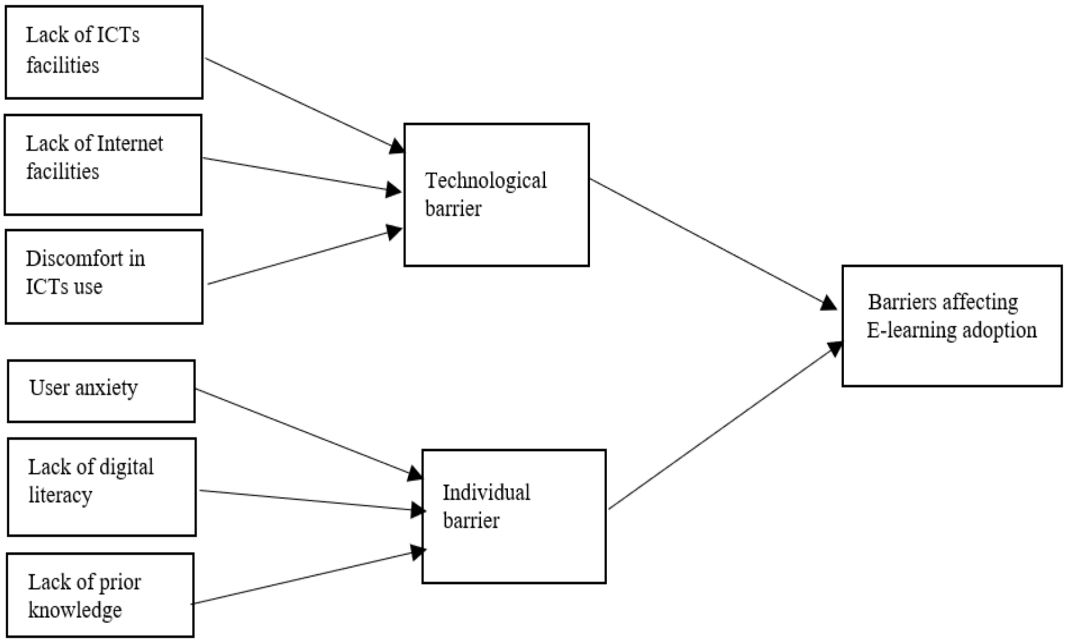


Figure 4.5: E-learning barrier – Research Model

The LPK consists of behaviour in a collaborative environment, Internet behaviour, and prior knowledge of the online course (Mohammadi, 2015; Eunjin et al., 2009). The IB includes lack of instructor and user ICTs skills, insufficient time for interaction, and improper guidance (Wiseman & Anderson, 2012; Petya et al., 2018). BEA includes the quality of hardware and software and e-learning tools.

Previous studies stated that the lack of ICTs, Internet facilities and discomfort of ICTs are important factors that reduce e-learning adoption. Inadequate ICTs facilities like hardware and software failure make users uncomfortable with e-learning services (Mohammadi, 2015; Deursen et al., 2017; Mariscal & Judith 2005; Zhong 2011). In addition, poor Internet connectivity, low quality of the Internet, and less Internet speed decrease user's interest towards online courses (Acharya & Lee, 2018; Hermeking, 2006). Thus, insufficient ICTs and Internet facilities increase the technological gap in the e-learning environment (Deursen et al., 2017). These factors reduce the user's willingness and interest towards e-learning adoption. Overall, it slows down the usage of the e-learning system. Therefore, the hypotheses are framed as:

H1: Lack of ICTs facilities is positively associated with technological barriers.
H2: Lack of Internet facilities is positively associated with technological barriers.
H3: The discomfort of ICTs use is positively associated with technological barriers.
H4: Technological barriers are positively associated with barriers affecting e-learning adoption.

A user's anxiety creates an individual gap in the online environment. Attitude towards e-learning, lack of ICTs skills, and inadequate use of the Internet increase the individual barriers in the online platform (Park et al., 2014; Deursen et al., 2015). Even though the instructor's motivation, interest, and ICTs skills encourage student participation in an online environment, improper guidance increases the individual gap. The user anxiety, lack of digital literacy and lack of prior knowledge increase technological barriers in the e-learning platform. Therefore, the hypotheses are developed as:

H5: User anxiety is positively associated with individual barriers.
H6: Lack of digital literacy is positively associated with individual barriers.

The lack of ICTs' literacy about the online course creates user anxiety and reduces the users. On the other hand, the users' prior knowledge about the course will increase the users' interest and encourage users to actively participate in the online course. It makes the user familiar with e-learning forums, e-learning tools, and other online resources. Thus, the lack of prior knowledge positively influences the lack of digital literacy (Sun et al., 2008; Barbeite et al., 2004). Therefore, the hypothesis is:

H7: Lack of prior knowledge is positively associated with individual barriers.

Insufficient ICTs and Internet resources that the users cannot easily access are the main causes of the technological barrier. The unequal distribution of digital resources also reduces individual participation in the online environment. The technological barrier negatively impacts the online course (Pearce & Rice, 2013, Kassab et al., 2015). On the other hand, lack of digital awareness increases user anxiety and decreases the interest of the individual. Hence, the individual barrier is considered as an important factor in the e-learning barriers (Van et al., 2015; Eunjin et al., 2009). Therefore, the hypotheses are framed as:

H8: Individual barriers are positively associated with barriers affecting e-learning adoption

In this study, the factors that influence e-learning barriers in Indian universities are identified and analysed. The drawback of the existing system is evaluated based on the technological and individual barriers.

4.4.2 Research method

With the help of literature, e-learning barriers in the Indian context have been identified. Even though India is a developing country, it is affected by technological barriers due to a shortage of digital resources (Puspitasari & Ishii, 2016). Thus, the lack of ICTs will reduce the effectiveness of e-learning systems in higher education institutions. In addition, lack of technological awareness about resource utilization also increases user anxiety and reduces the outcome of e-learning. It is important to understand that digital resource availability will increase the user's attitude towards e-learning adoption. Therefore, both the technological and individual barriers have been equally considered to overcome the e-learning barriers.

Based on the literature review, various constructs of the study were identified. This consists of constructs that are used to measure the technological barrier (3), individual barrier (3), and barriers that affect e-learning adoption (3). Overall, nine constructs, including the digital divide in e-learning, were finalized for the study. Next, a pilot study was carried out using 50 students to check the clarity of the questionnaire. Based on feedback, the structure and language of the questionnaire were modified.

The hyperlink of the online questionnaire was sent via email and social media to all graduate and undergraduate students in higher education institutes. Additional information like the objective of the survey and contact details of the researchers were also provided in the questionnaire in case the respondents needed any further clarification. On the other hand, the approval of university authorities was taken to collect offline survey data directly from college premises. The details were updated regularly to coordinators and principals of higher education institutions. In the questionnaire, it is clearly mentioned that no personal information was elicited and that there was no monitoring system. Hence, all information collected was remained anonymous and to be used only for research purposes.

This study included all higher education institutions, including central government, state government, and private colleges.

The questionnaires were finalized with the help of extant literature support and expert opinion (Appendix B) and consisted of the five-point scale starting from strongly disagree (1) to strongly agree (5). It also included demographic details of users, including gender, age, type of organization, and e-learning platforms familiar to respondents, as shown in Table 4.1. The study mainly focused on e-learning barriers factors that affect e-learning adoption.

The analysis was carried out through the Structural Equation Model (SEM). The Partial Least Squares SEM (PLS-SEM) method was chosen to estimate the relation between the latent variable in the proposed model. It also measures properties and tests the hypothesis using a component-based estimation approach (Hair et al., 2012; Ringle et al., 2012; Straub et al., 2012; Tarhini et al., 2013). Many researchers suggest this method because of its flexibility in data usage, model complications, and related description. PLS-SEM provides advanced features compared to the covariance approach (Marko et al., 2014; Teo, 2011). This method helps to construct a model to measures accuracy without any complexity.

4.4.2.1 Measurement Model Analysis

The constructs were established using reflective indicators. By using the standard deviation rule, the following measurements were tested: Factor loading, Variance Inflation Factors (VIF), Cronbach's alpha (CA), Composite Reliability (CR), Average Variance Extract (AVE), and Discriminant Validity (DV). The loading factor was estimated to identify weak items in the model. The multicollinearity test is done to find a correlation among variables. The cut-off value of VIF is below 10 (Alathur et al., 2016). In this study, the VIF values were significant, and thus multicollinearity test results were satisfied.

Cronbach’s Alpha was used to analyze the internal consistency of the model. If the total item score of the constructs was above 0.700, it indicated that all items had the same scope and it satisfied internal consistency (Peter, 1979). Meanwhile, CR was also evaluated in this study to get the accuracy of the model. The significant value was above 0. 07, it was also satisfied with the study (Henseler, 2010). Finally, AVE was measured to fulfil the convergent validity test. According to Segers (1997), the value should be greater than 0.500 to satisfy this test. In our study, AVE values are above 0.500; hence AVE is also satisfied.

In this study, an empirical test was carried out using PLS-SEM (Ringle et al., 2014). The online and offline data were collected (704 valid responses) from both graduate and undergraduate students to perform the empirical analysis. The dataset consists of 71% male students, and the remaining 29% were females. The average age of students participating in the survey was 25 years. Among these, 63.5% of students belonged to central government colleges, 20.6% of state government colleges, and 16.0% of private institutions. All respondents had attended at least one online course previously, and they are familiar with e-learning. The measurement model analysis is shown in Table 4.10.

Table 4.10: Measurement Model Analysis

Latent Variable	Factor loading	CA	CR	AVE
Lack of ICTs facilities	0.826	0.913	0.936	0.786
	0.941			
	0.929			
	0.845			
Lack of Internet facilities	0.739	0.880	0.914	0.729
	0.952			
	0.932			
	0.770			
Discomfort of ICTs use	0.765	0.860	0.903	0.701
	0.786			
	0.890			
	0.901			
User Anxiety	0.935	0.928	0.949	0.823
	0.947			
	0.891			
	0.853			
Lack of Digital Literacy	0.900	0.916	0.941	0.799
	0.896			
	0.898			
	0.882			
Lack of Prior Knowledge	0.917	0.886	0.929	0.813
	0.891			
	0.897			
Technological Barriers	0.949	0.941	0.962	0.894
	0.939			
	0.948			
Individual Barriers	0.923	0.936	0.954	0.839
	0.936			
	0.913			
	0.891			
Barriers affecting E-learning adoption	0.907	0.859	0.914	0.780
	0.905			
	0.836			

The VIF values range from 1.749 to 6.276 and are in the acceptance range (<10.00). This indicates that all the variables are highly correlated with each other. The CA values were between 0.859 and 0.947, with the lowest value being 0.859 between the acceptance range. Hence, all variables interrelated with other items and reliability were achieved. Composite reliability measures the overall reliability of heterogeneous and similar items in the model. The CR value lies between 0.903 and 0.962. Thus, the overall reliability was satisfied. Finally, AVE values were assessed (low = 0.701 and high = 0.894) and were found to be greater than the acceptable value of 0.5. Therefore, this model satisfied the reliability test, and all items were included in further analysis.

4.4.2.2 Assessment of the structure model

In the assessment of the structure model, the relationship between constructs was tested to validate the measurement model. The latent variable deviation determines the quality of the proposed model. The latent variables used in this analysis were technological barriers ($R^2 = 0.249$), individual barriers ($R^2 = 0.295$), and barriers affecting e-learning adoption ($R^2 = 0.712$). This model explained 71.2% of the dependent variable 'barrier affecting e-learning adoption' in Indian universities. The result shows that both technological and individual barriers together reduce the performance of e-learning systems, and thus it directly affect e-learning adoption.

Path Analysis

Path analysis was carried out to identify how the independent variable affected the dependent variable in the model (Henseler et al., 2014). The barriers affecting e-learning systems were evaluated using a path coefficient, i.e., the R^2 value is 0.712. Thus, the technological barriers and individual barriers explained 71% of the variance in the construct 'barriers affecting e-learning adoption'. The path analysis result is shown in Table 4.11.

Table 4.11 Hypothesis, path coefficients, significance and hypothesis support

Latent Variables	β value	p-value	Findings	Support
Lack of ICTs facilities -> Technological Barriers	0.042	0.392	positively and statistically insignificant	No
Lack of Internet facilities -> Technological Barriers	0.011	0.771	positively and statistically insignificant	No
Discomfort of ICTs use -> Technological Barriers	0.484	0.000	positively and statistically significant	Yes
User Anxiety -> Individual Barriers	0.411	0.000	positively and statistically significant	Yes
Lack of Digital Literacy -> Individual Barriers	0.082	0.137	positively and statistically insignificant	No
Lack of Prior Knowledge -> Individual Barriers	0.070	0.406	positively and statistically insignificant	No
Technological Barriers -> Barrier Affecting E-learning adoption	0.650	0.000	positively and statistically significant	Yes
Individual Barriers -> Barrier Affecting E-learning adoption	0.244	0.010	positively and statistically significant	Yes

‘Technological barriers’ (TB) is explained by 24% with three constructs: lack of ICTs facilities, lack of Internet facilities, and discomfort of ICTs. ‘Individual barriers’ is explained by 29% with the three constructs: user anxiety, lack of digital literacy, and prior knowledge.

The Lack of ICTs facilities (LICTs) (β = 0.042; $p > 0.05$) does not significantly influence the TB. The analysis shows that there are sufficient ICTs facilities available in India. It is because the government of India launched many schemes to enrich the e-learning infrastructure facilities. Next, the lack of internet facilities (β=0.011; $p > 0.05$) is insignificant, representing that the Internet facility does not affect ICTs usage. The respondents are satisfied with the Internet facilities available during the online course. The DICTs also has a positive influence on TB (β=0.484; $p < 0.001$). It implies that a lack of physical access to ICTs increases the technological barrier in the e-learning platform. Finally, the technological barriers positively influence e-learning adoption (β=0.650; $p < 0.001$). From this, it is confirmed that the technological barrier in the e-learning environment decreases the performance of e-learning systems.

The findings show that the individual barrier is the main reason for the improper utilisation of online resources. This also increases the operational cost of e-learning services and makes more complications in maintenance. The construct ‘user anxiety’ (UA) is positively significant with the individual barrier (β= β=0.411; p=0.000). It implies that user anxiety will increase the individual barrier in the e-learning platform. The summary of the hypotheses is shown in Table 4.12.

Table 4.12 Summary of hypotheses

Hypothesis	Hypothesis statement	Result
H1	Lack of ICTs facilities is positively associated with technological barriers.	No
H2	Lack of Internet facilities is positively associated with technological barriers	No
H3	The discomfort of ICTs use is positively associated with technological barriers	Yes
H4	Technological barriers are positively associated with barriers affecting e-learning adoption	Yes
H5	User Anxiety is positively associated with individual barriers.	Yes
H6	Lack of digital literacy is positively associated with individual barriers.	No
H7	Lack of prior knowledge is positively associated with individual barrier	No
H8	Individual barriers are positively associated with barriers affecting e-learning adoption	Yes

The Lack of Digital Literacy (LDL) is not positively associated with the individual barrier (β=0.082; p=0.137). The lack of digital literacy does not affect the individual barrier in e-learning because the government of India introduced many awareness programs and camping through Digital India scheme. The lack of prior knowledge (LPK) is not positively associated with the individual barrier (β=0.070; p=0.406). It implies that the e-learning courses are well structured and provide a flexible online platform for the users to navigate. UA (β=0.411; p=0.000), LDL (β=0.082; p=0.137) and LPK (β=0.070; p=0.406) have a positive influence on IB. This study concludes that individual barriers and technological barriers affect e-learning adoption and reduce the performance of e-learning systems (Dijk 2003, Lee et al., 2014; Pearce & Rice, 2013; Van et al., 2015; Kassab et al., 2015, Parayitam et al., 2010). Overall, the discomfort of using ICTs and user anxiety are considered as the main reasons for the e-learning barriers in India (Abhiyendra, 2007; Deursen et al., 2017; Gunkel, 2003; Mariscal & Judith, 2005; Zhong, 2011; Bagchi, 2005; Hermeking, 2006). Therefore, hypotheses H3, H4, H5, and H8 were supported, and H1, H2, H3, H7 were not supported.

4.4.3 Discussion

The current study identifies various e-learning barriers for e-learning adoption in the Indian context. The proposed model identifies the level of technological and individual barriers among users in higher education institutions. It mainly focuses on the user and technological perspective and considers factors associated with the e-learning barriers. The goal of this paper is to identify the e-learning barriers faced by Indian higher education institutions. Although recent relevant studies have identified barriers, there are fewer studies reported in the Indian context.

The strength of this study was that it identified the effect of various barriers in e-learning, especially in higher education. The study was conducted among higher education students because e-learning is considered as a fundamental part of the learning experience. Much research has been conducted in the last two decades to analyze the interest of students in higher education (Robert et al., 2009; Bliuc et al., 2007; Salmon, 2002). However, previous studies mainly focused on students' experience in e-learning and suggested solutions to improve general outcomes. It also compared e-learning with traditional learning and identified key aspects of students' experience.

In this study, an empirical test was conducted, and critical factors that affect e-learning adoption are identified. The results revealed that the improper distribution of digital resources caused the technological barrier, thus slowing down e-learning usage. In addition, lack of digital literacy and awareness also created an individual barrier among users. Although the results of the current study support previous research work on the e-learning barrier, it also extends these works on many levels. First, this study found the technological barriers faced by higher education users in the e-learning platform. Both telecommunication and Internet facilities were included in the study. Secondly, the findings identified the limitations of the e-learning barrier from the user perspective. The lack of digital literacy and awareness were evaluated based on previous experiences. Thirdly, the influence of the technological and individual barrier was measured to analyse their effect on e-learning adoption.

The lack of digital literacy and lack of prior knowledge does not influence individual barriers in this study. This is because even though the users may have awareness about e-learning, they may not be comfortable to use e-learning due to anxiety. Thus, user anxiety is considered as an important factor that influences individual barriers. On the other hand, the discomfort of ICTs use is the root cause that increases the technological barrier. Without sufficient ICTs facilities, it is not possible to solve the technological barrier in e-learning. This study identified that the technological barrier is the most influential factor in e-learning adoption. Researchers from different countries also identified the same results (Wiseman & Anderson, 2012; Julian et al., 2008; Gibson et al., 2014; Yu et al., 2014). In addition, Internet facilities are not considered as a technological barrier in the study because the Internet penetration rate is more in India.

4.5 Study 4- Cloud-based E-learning

4.5.1 Simulation of an E-Learning in CloudAnalyst

A good quality online course requires sufficient Internet connectivity and the best quality video/graphics cards. To solve the cloud adoption problem, synchronous tools are used. In the simulation environment, different zonal time intervals were clearly defined. Most nations, including India, are facing inadequate infrastructure and Internet bandwidth as an e-learning barrier (Chawla & Joshi, 2021; Rao, 2011). When e-learning provides a synchronous mode of online courses, zonal timing is also considered a critical factor. Therefore, online synchronous tools are used to create an active online environment. In this study, the cloud-based online environment is created using the CloudAnalyst simulation tool. There are predefined options available to create a live online environment in the CloudAnalyst tool.

Cloud Analyst is a tool that allows developers to simulate large-scale Cloud applications in order to better understand their performance under various deployment configurations. Basically, Cloud Analyst is a Cloudsim (Goyal et al., 2012; Hicham et al.,2016) based Graphic User Interference (GUI) tool used for modeling and analysis of large-scale cloud computing environment. It is made for evaluating performance and cost of large scale geographically distributed cloud system that is having huge user workload based on different parameters. It enables the modeler to execute the simulation repeatedly with the modifications to the parameters quickly and easily. It has an attractive GUI facility and flexibility to configure any geographically distributed system such as setting hardware parameters i.e., storage, main memory, bandwidth etc. It gives the simulation results in terms of chart and table that includes cost, response time, datacenter processing time, and load over datacenter etc. (Malhotra & Jain, 2013; Hicham, G.T. & Chaker, 2016; Humane & Varshapriya, 2015).

The Cloud Analyst help enhance load balancing algorithms and experimentally verify how to minimize the response time and processing time. This learning would provide valued understanding to design infrastructure services of the Cloud. Different areas like coordination between one data center and other data center, algorithms of load balancing as well as other value-added services are also considered. The various scheduling algorithms available in Cloud Analyst are Round Robin scheduling algorithms, Equally Spread Current Execution and Throttled load balancing policies (Ahmed & Singh, 2012). The current study utilises Round Robin scheduling algorithms. In this algorithm, it uses principle of time slices which divides the time into multiple slices and each node is given a particular time slice or time interval. Each node is given a quantum and in this quantum the node will perform its operations. The resources of the service provider are provided to the requesting client on the basis of this time slice (Patel & Patel, 2015; Singh et al., 2016; Mishra & Bhukya, 2014).

The CloudAnalyst uses different region IDs to represent six different continents. The region ID for “North America-0, South America-1, Europe-2, Asia-3, Africa- 4, and Australia & Oceania-5” (Meftah et al., 2018; Mezcal et al., 2018). In this study, the users who registered for a popular e-learning service in Asia is simulated. This is because India has the highest number of e-learners next to the US. This study focuses on the e-learners’ who register for an online course from India. Therefore, the online platform is simulated according to the Asian zonal time. It is assumed that online users are active 7 hours per day between the time interval of 13.00 and 22.00. By default, it is expected that 1/10 of the users are active during peak hours and off-hours. It is assumed that online users are activated 7 h per day between the time interval of 13.00 and 22.00. By default, it is expected that 1/10th of the users are active during peak hours and off-hours. In this study, half of the learners' population is considered. Only 15,00,000 online learners are reflected in the cloud-based e-learning simulation environment.

4.5.2 Result Analysis

The configuration setup for the CloudAnalyst is subdivided into three steps. In step-1, the main configuration user base is configured. In step-2, the datacenter configurations are performed. In step-3, an advanced configuration like grouping factors is configured. Both models use the same simulation environment except the data centre configuration.

In step-1, the main configuration first, the simulation time is set as 60 min. The user base name UB4 for region 3 is configured with 15,000 average peak users. 1/10 of the average users is assumed as average off-peak users. The data size request is 1000 bytes with peak hours 15.00–22.00. The application deployment is configured with 50 virtual machines (VM) with 1000 MB of available bandwidth and memory.

In step-2, the data centre is configured with Xen-VMM with LINUX-OS, ×86 architecture. The cost for hosting Coursera in the e-learning environment is: "cost per VM$/hr is 0.1, memory cost$ is 0.05, storage cost$ is 0.1 and data transfer cost$/Gb is 0.1" with one physical hardware unit (Meftah et al., 2018). The physical hardware details of the data centre consist of 2 GB memory with 10 × 100 GB dual-channel SAS disks of storage. The number of processors is 4 with 10000 processing speed with VM time-sharing policy.

4.5.2.1 Single Datacentre

The online course Coursera is hosted on a single data centre and analysed in Case 1. It is deployed in region 3 (Asia). The data centre consists of 50 VM with each consisting of 1024 MB memory. The processing speed of VM is 37006 million instructions per second (MIPS). Based on this setup, the simulation is run, and results are obtained. The overall response time summary is shown in Table 4.13.

Table 4.13 Summary of response time and processing time – Single data centre

	Aver (ms)	Mini (ms)	Maxi (ms)
Overall response time	239.89	108.39	329.17
Data centre processing time	181.86	56.36	268.11

Table 4.14 Response time of UB based on region 3– Single data centre

	Aver (ms)	Mini (ms)	Maxi (ms)
UB4	239.89	108.39	329.17

Table 4.15 Request servicing times of Single data centre

	Aver (ms)	Mini (ms)	Maxi (ms)
Data centre 1	181.86	56.36	268.11

Table 4.16 Cost estimation – Single data centre

	VM cost$	Data transfer cost$	Total$
Data center 1	1 5.00	2129.31	2134.31

The userbase hourly average response time is measured for UB4. It analyses how the peak load of the userbase (UB4) is distributed for the time period of 7 hours. The peak time of the userbase varies according to the zonal time. The simulation result shows the hourly average response time of the userbase for the region.

The user base response time by region is analysed, and the results are displayed in Table 4.14. The average time, minimum time and maximum time of the user base is calculated based on region-3. The data centre's request servicing time is measured based on the user request. The data centre request servicing time is displayed in Table 4.15. The VMcost and data transfer cost are combined together to estimate the cost. The total cost estimation of a single data centre is shown in Table 4.16.

4.5.2.2 Multiple Datacentre

When online users are more, then the service provider uses multiple data centres. The main purpose of multiple data centres is to decrease the response time and increase the quality of e-learning services. All the cloud setups are the same as single data centre; only one more data centre is added in the simulation environment. The 50 VM is split into two half and given to two centres. The overall response time and processing time of the data centres are shown in Table 4.17.

Table 4.17 Summary of response time and processing time – Multiple data centre

	Aver (ms)	Mini (ms)	Maxi (ms)
Overall response time	149.37	68.03	257.24
Data centre processing time	92.08	15.77	198.58

Table 4.18 Response time of UB based on region 3– Multiple data centre

	Aver (ms)	Mini (ms)	Maxi (ms)
UB4	149.37	68.03	257.24

Table 4.19 Request servicing times of Multiple data centre

	Aver (ms)	Mini (ms)	Maxi (ms)
Data center 1	92.50	15.77	198.58
Data center 1	91.67	15.78	197.60

Table 4.20 Cost estimation – Multiple data centre

	VM cost$	Data transfer cost$	Total$
Data center 1	2.50	1070.30	1072.81
Data center 2	2.50	1059.00	1061.50

The overall response time of the multiple data centre is significantly less compared to the single data centre. This is because an additional infrastructure facility is available for the online course. The closest data centre's service broker policy is the main reason for the improvement. The data centre with two different locations provides an easily accessible facility to the learners. Thus, the efficiency of the e-learning course is improved in multiple data centre model. The response time by region is shown in Table 4.18.

The requesting service time of the multiple data centres is calculated based on the user request. The data centre average, minimum and maximum time is shown in Table 4.19. The overall cost estimation of the infrastructure service is calculated based on VM cost and data transfer cost in multiple data centres. The total cost estimation is shown in Table 4.20.

According to the simulation result, the average processing time of the data centre is increased due to multiple VM. On the other hand, the distribution of VM to two different data centres increases the peak loading time in both centres. Thus, traffic time is less in model-2 compared to model-1. In multiple data centres, the data loading traffic value is less.

4.6 Conclusion

Many higher education institutions shift from traditional learning to e-learning to improve their education quality. According to Islam and Azad (2015), e-learning does not substitute for traditional learning, and it is to be instead considered as a tool to improve the scope of learning. Several studies discussed e-learning adoption in higher education institutions and determined user intention, perceived usefulness and satisfaction as e-learning adoption factors (Boateng et al., 2016; Cheung & Vogel, 2013; Merhi, 2015). In a developing country like India, implementing a quality e-learning system has remained a problem because it is challenging to design an e-learning system according to individual needs. As a result, standard attributes from previous studies are established, and additional parameters are added to improve online learning. Also, the research will highlight technology and learner dimensions to increase e-learning adoption in India.

There are some major implications drawn from our findings on gender-based e-learning adoption. The study concludes that user attitude, technology awareness, perceived satisfaction and user behaviour play a vital role in gender-based e-learning adoption. Therefore, these four constructs are added under constructivism. This is because previous studies identified that user behaviour and collaboration were not well-structured under constructivism. In addition, findings also identify the gender gap in e-learning adoption in the Indian context. Therefore, to improve e-learning adoption, a conceptual model is proposed with new constructs. The findings of the study also confirm that there is a gender gap in the Indian context. Therefore, e-learning adoption is analysed using gender differences.

The e-learning barrier is categorized into two categories such as technological and individual barriers. Even though India has adequate facilities and Internet service, it is suffering from e-learning barriers. Lack of government policies and insufficient funds are also considered as important barriers in e-learning. Due to lack of awareness about ICTs, many resources are wasted in urban areas. On the other hand, there are no proper guidelines for rural people to use digital resources efficiently. These barriers affect e-learning adoption in the Indian context.

With the help of literature, it is identified that the infrastructure is a critical factor that influences e-learning adoption. Hence, the cloud-based e-learning system is deployed using cloud simulator and the infrastructure facilities such as data storage is simulated using the CloudAnalyst tool. Both single and multiple data centre setup are established. The response time and processing time were estimated and compared between the two models.

The quantitative method is used to analyse factors influencing e-learning adoption and gender-based e-learning. In addition, the e-learning barriers were identified and analysed through this study. Finally, the cloud-based e-learning environment is deployed using simulator tool, and the infrastructure service is analysed from a management perspective.

CHAPTER 5

QUALITATIVE STUDY

Chapter 5

Qualitative Study

5.1 Introduction

This chapter explains various qualitative analysis conducted in this study. Initially, this chapter utilises sentiment analysis as a qualitative method to prioritise the barriers identified in Chapter 4. Infrastructure was identified as the most prominent barrier from the findings of the sentiment analysis. Therefore, this qualitative study further analyses the e-learning platforms with case studies of existing initiatives (research objective 3). Two case studies are conducted to examine the mobile platform ability to promote e-learning services. First, an interview-based case study on a special school is carried out to determine the advantages of mobile apps over standard Assistive Technology Devices (ATDs). Second, using Twitter Sentiment Analysis, the level of awareness of mobile apps for civic learning and e-learning is measured, and the results are compared.

This chapter is structured as follows. Section 5.2 deals with prioritizing e-learning barriers through sentiment analysis. Section 5.3 analyses the process of data collection, data analysis, and results involved in the qualitative study of special education. In section 5.4, the sentiment analysis of mobile assist e-learning is discussed. Finally, section 5.5 concludes this chapter.

5.2. Study 5-E-learning barriers (Sentiment analysis)

Sentiment analysis is a technique used to extract the opinion or feedback of the users from the information system. It is considered as an advanced version of data mining techniques. In sentiment analysis, the users' opinions are extracted as a statement from the social media database (Udanor & Anyanwu, 2019; Bozanta & Kutlu, 2018). In this study, the lexicon analytic technique was used to extract opinions in polarity values from the database (Quan & Ren, 2014; Shahzad et al., 2017).

Many researchers perform sentiment analysis to extract the opinion of the users (Udanor et al., 2016; Butts, 2008). Therefore, in this study, the sentiment analysis was carried out to measure user's awareness of mobile apps. Three civic learning apps and three e-learning apps were analysed in this study. Social media analytics, such as Twitter and Facebook analysis, is utilised by researchers to analyse the individual opinion of the users within the particular domain (Jennifer, 2015). Thus, the present study adopts social media analysis to collect and analyse secondary data. In our study, the Twitter database has been chosen to perform this analysis.

R tool is an open-source programming tool used to perform sentiment analysis. The sentence-level polarity sentiment is extracted from the Twitter database (He et al., 2011; Chang et al., 2019). The recent tweets were collected using hashtags. Finally, the opinion of the users is aggregated into different polarities and emotions (Udanor & Anyanwu, 2019).

In this study, the tweets from India are collected based on geocoding. The Twitter SA is carried out to find the most significant challenge in e-learning. Approximately every tweet consists of 0.47 emotion tokens in the text. Therefore, emotion tokens are taken to perform Twitter SA, which express the positive or negative feeling about the users' opinion (Denker et al., 2013; Ribeiro et al.,2010).In particular, this study includes the English language tweets collected from online courses like course, Edx, and NPTEL. The hashtags like #infrastructure, #Internet, #software/hardware and #digital divide is used. The topics and hashtag are listed in Table 5.1.

Table 5.1: Topics and hashtags selected for this study

Topic	Hashtag
Infrastructure	#elearninginfrastructure, #infrasrtucture
Internet	#internet, #elearninginternet
Software/hardware	#elearningsoftware, #elearninghardware
Digital divide	#elearningdigitaldivide

On Twitter, users can express their feelings without any constraints like language, abbreviation, alternative spelling, and grammatical errors Van et al.,2005. Therefore, manual data cleaning is required to identify common errors. The extracted data normalised, typical errors and alternating spelling were corrected for future processing. The sample tweets were shown in Table 5.2.

Table 5.2 Sample Tweets

Topic	Tweets (example)
Infrastructure	You are on the front lines of a #cyberwar, targeting our critical infrastructure and networks. Learn about the there… https://t.co/MOQk84a7mS
Internet	"97% of low-income students rely on school for internet access, but 40 million students do not have high-speed Inter"… https://t.co/NCPuFO6xZi
Software/hardware	Unable to create software simulation #elearning https://t.co/hmvvY3iHUo
Digital divide	Three Signs Your Class Is Suffering from the Digital Divide https://t.co/3IxNpR2sr5 #edtech #stem #pbl #k12 #ece… https://t.co/WqBUOBQNt9

The dataset is executed based on the lexicon of sentiment words using SentiStrength. The rule-based approach identifies the opinion lexicon in the text and classifies them as positive/ negative words. Finally, two scores were assigned for each tweet: Positive sentiment score [1 to 5] and negative sentiment score [-1 to -5]. These scores reveal the mixed emotions of users (Golbeck et al.,2010; Graham et l.,2016; Suresh et al.,2019)

In addition, The NRC emotion lexicon words with "six basic emotions (anger, fear, anticipation, trust, surprise, sadness, joy and disgust) and two sentiments polarities (positive and negative)" are used in this study (Subasicet et al.,2001; Taboada et al.,2011; Ribeiro et al.,2010).In addition, SentiStrength and NRC dictionary extracts the sentiment polarities and construct emotion vectors (Liu 2016; Bagchi 2005). The simple random sampling method was used to collect data from Twitter social media. To collect data, a connection is established with Twitter, and appropriate keywords were used. Different keywords used to extract data are shown in Tables 12a and 12b. The approach, which is used to analyse sentiments of Twitter content. Four different steps, namely extracting tweets, cleaning tweets, generating sentiment score for each tweet and finding polarity of tweets (Ema 2018; Van 2005) were performed as a part of sentiment analysis. The entire approach for sentiment analysis is implemented in the R programming language.

The sentiment analysis technique is a predictive measure and is mostly used in education sectors. The study focuses on two different sentiment analysis techniques, such as lexicon-based and Naive Bayes approaches. Using these approaches, the individual tweets can be labelled as positive or negative in polarity. Furthermore, these approaches can look for positive words in negative reviews and vice versa (Leong et al.,2012; Sally et al.,2019).

In this study, the polarity of the text is analysed based on the lexicon-based approach (Taboada et al.,2011). Previous studies used a single approach to analyse the emotions of the users. To analyse both the content and connectivity pattern of the users, the machine learning approach is integrated with lexicon-based approach (Kundi et al.,2014; Bo and Lee 2008).After analysis, the result will be taken into account to fill the technological gap in the e-learning service.

5.2.1 Analysis of Results

Lexicon based approach:

The lexicon-based method is used to extract the sentiment from the textual message on the Twitter dataset. Then the sentiment score is calculated based on the polarity classifier. Each bag-of-words is compared to the lexicons, and the polarity value is assigned for each tweet. Finally, thetotal polarity is calculated for the whole dataset (Turney &Peter 2006).In this study, the SentiWordNet was used to extract the words from the Twitter dataset. The subjective score is assigned as positive, negative and neutral polarity (Ohana & Tierney 2009). The frequency is calculated based on the polarity value, and it is shown in Figure 5.1.

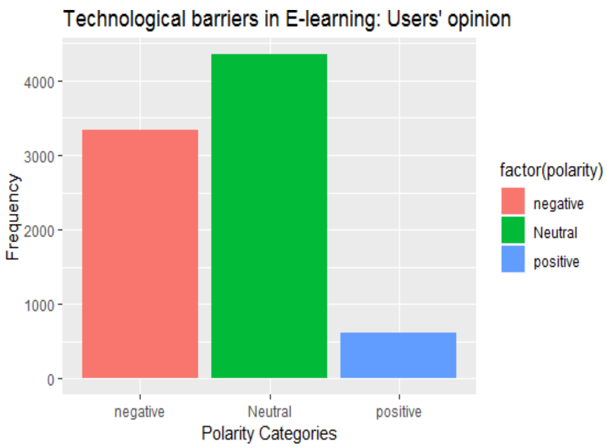


Figure 5.1: Technological barriers in E-learning

The number of positive and negative tweets occurrencesis calculated on the training data set. For example, the word dislike carries a negative sentiment. In some cases, the words have both positive and negative sentiment, which is classified as neutral. According to Wiebe et al.,2005, negative polarity of each word is calculated as “the number of negative sentences divided by the total number of sentences”. Based on the same strategy, the polarity of the tweets is categorised (Ribeiro et al.,2010; Silva et al.,2009; Khan et al.,2014).

Word analysis:

The word analysis extracts the words that are discussed frequently by the users on the Twitter platform Chauhan et al.,2016. The most popular words related to e-learning challenges, excluding the hashtags used in Twitter, are infrastructure (5999), Internet (5986), Software/hardware (852), and digital divide (768). Totally, 13,605 tweets were extracted from the Twitter dataset. The online users discussed more the infrastructure and Internet issues. The word analysis is performed based on the themes and polarity values. The word analysis is categorised based on three polarity values: positive, neutral and negative (Ding 2011; Miller et al.,2014). The result of the word analysis is shown in Table 5.3.

Table 5.3: Twitter-based sentiment analysis (classification by polarity)

Factors/themes	Polarity		
	Negative	Neutral	Positive
Infrastructure	3777	1098	1124
Internet	3244	1046	1696
Software/Hardware	85	727	40
Digital divide	126	607	35

The percentage of e-learning barrier topics discussed through Twitter are infrastructure = 44%, Internet = 43%, software/hardware = 6%, and digital divide = 5%. The Twitter-based SA result is shown in Figure 5.2.

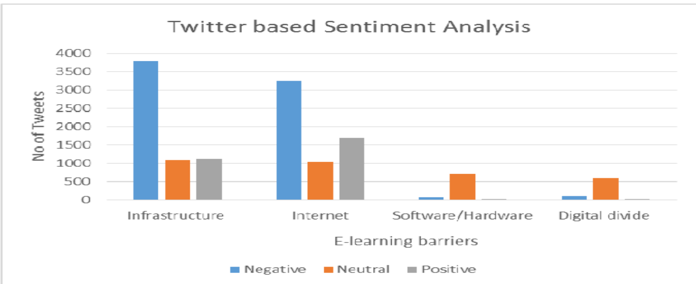


Figure: 5.2 Twitter-based sentiment analysis result

Among these, the negative polarity is highest, followed by positive polarity. Thetotal number of tweets counted under negative polarity is 7232 (52%), positive is 2895 (38%), and neutral is 3478 (31%).

5.2.2 Analysis of e-learning challenges based on themes

The tweets were collected under four different themes: infrastructure, Internet, software/hardware, and digital divide (Ding 2011). Based on SA– classified by polarity and the emotions of the users are identified (Miller et al.,2014). The infrastructure and

Internet are considered critical factors because the negative sentiments are high for both. This implies that the online users are not satisfied with the infrastructure and Internet facilities provided for the e-learning process. The neutral sentiment is more on software/hardware and digital divide factors.

Machine learning approach:

In this study, the machine learning approach is used as predictive analytics on the Twitter data set. Different techniques have been used in supervised learning to analyse user sentiments Cortes et al., 1995. Some of them are Naive Bayes (NB), Support Vector Machine (SVM), Neural Network (NN), and Maximum Entropy (Cambria et al.,2013; Pietro et al.,2019; Ismail et al.,2018) in which the NB approach is used to perform SA in this study.

Emotion detection using Naive Bayes algorithm

In this study, the NB algorithm with a sentiment package (R tool) is used. The various emotions are detected from the Twitter data set. Therefore, each tweet is analysed, and the occurrence of emotions is estimated. The different emotions used along with the polarities are joy, surprise, anger, sadness, disgust, and fear (Hashem et al.,2015; Symeonidis et al.,2018). The polarity measure of six emotions is analysed, and the result is shown in Figure 5.2.

RapidMiner software tool was utilized to measure the performance of the model in the study (Arunadevi et al., 2018). Using Naive Bayes algorithm, each emotion is analyzed separately. In figure 5.3a, polarities in the anger emotion are identified as positive = 37%, neutral=8% and negative=55%, which indicates that the users are not satisfied with the online platform as they expressed their negative polarity more. In figure 5.3b, the polarities in the disgust emotion are identified as positive= 33% and negative=67% which indicates that the online users are not comfortable with the e-learning platform. In figure 5.3c, the polarities in the fear emotion are identified as negative=100%, which denotes that inadequate infrastructure might be inducing fear emotion among the users.

In figure 5.3e, polarities in the sadness emotion are identified as positive = 4%, neutral=11% and negative=85%, which could be due to the unstable internet connection while using e-learning. In figure 5.3d, polarities in the joy emotion are identified as positive = 71%, neutral=17% and negative=12%, which indicates that some of the users might be finding e-learning as convenient and flexible mode of learning. In figure 5.3f, polarities in the surprise emotion are identified as positive = 63%, neutral=12% and negative=25%, which denotes the exciting and interesting aspects of e-learning.

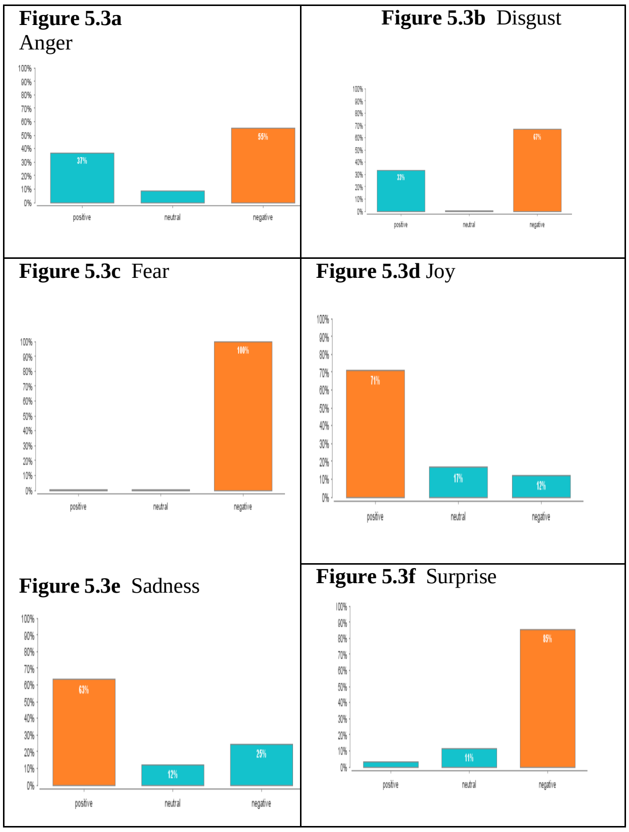


Figure 5.3: Emotion Detection Using Naive Bayes Algorithm

The emotion classifier in sentiment analysis helped in understanding the emotion of users related to e-learning adoption. For instance, anger and sadness are used to express the negative emotions of the users towards e-learning adoption. Twitter analysis performed in the current study revealed that a significant number of tweets indicated that users face lack of infrastructure and internet access. Many of the students relies on their educational institutions (such as schools, colleges etc) for internet facilities. There exist unequal distribution of internet facilities in the country. These could be inducing emotions such as anger and sadness among students as they might be insecure about their access to proper infrastructure and internet facilities. The same have been pointed out by the recent studies conducted in e-learning context by Balachandran et al. (2020) and Khadse et al. (2022).

The emotion score percentage was calculated following machine learning approach. As a result, the negative polarity is higher for anger, disgust, fear, and sadness. The positive polarity is high for joy and surprise. For angry the emotion percentage is (positive = 37%, neutral = 8% and negative=55%), disgust (negative=67%), fear (negative= 100%), joy (positive = 71%, neutral=17% and negative=12%), sadness (positive = 4%, neutral=11% and negative=85%), and surprise (positive = 63%, neutral=12% and negative=25%). The emotion-based result is shown in Table 5.3.

Table 5.3: Twitter-based sentiment analysis (classification by polarity)

Emotion	Positive	Neutral	Negative
Anger	37%	8%	55%
Disgust	33%	-	67%
Fear	-	-	100%
Joy	71%	17%	12%
Sadness	4%	11%	85%
Surprise	63%	12%	25%

Performance Measures:

In this study, the confusion matrix is used to describe the performance of the model. This matrix is constructed on a set of test data with known true values. It consists of two classes, namely actual and predicated classes. Based on these two classes, four parameters are formed. They are "true positive, true negative, false positive and false negative". The true positive (tp) have correctly predicted positive values in both the actual and predicted class. The truenegative is correctly predicted negative values in two classes. In the case of false positive (fp) and false negative (fn) parameters, both have contradicted values in actual and predicted classes (Grcar et al.,2017). "Precision is the ratio of correctly predicted positive observation of the total predicate positive observations (Ismail et al., 2018). The precision is measured by:

Precision = "tp/tp+fp" ----------------- (1) Ismail et al., 2018.

The recall represents the "ratio of correctly predicted positive observation of all observations in actual class on positive values" (Saifa et al.,2016) The recall is measured by:

Recall= "tp/tp+fn" -------------------------- (2) Saifa et al.,2016

The accuracy is defined as "a ratio of correctly predicted observation to the total observations". Therefore, the performance of the system is measured through accuracy (Aleksey et al.,2015). The formula to calculate the accuracy is:

Accuracy = "tp+tn/tp+tn+fp+fn" -------- (3) Aleksey et al.,2015

The precision, recall and accuracy results are shown in Table 5.4.

Table 5.4: Naïve Bayes model: precision, recall and accuracy values

Class precision		**Class recall**		**Accuracy**
pred.positive	59.90	true.positive	98.86	60.2%
pred.negative	68.42	true.negative	14.36	

The confusion matrix consists of two classes (Actual and Predicted class) and four parameters (predicated positiveand negative, true positive and negative). In our model, the precision rate is 59.90% (pred. positive) and 68.42 (pred negative), while recall rate are 98.86 (true positive) and 14.36 (true negative). All the values are above 0.5, which denotes the proposed model is good. The overall accuracy measured through the NB model is 60.2%.

5.3 Study 6- Special Education

This study is based on interviews conducted among special students, teachers, and institutions in the special education sector. The participants in this study are special students with various disabilities and teachers who have the experience to handle the special students (Hanne et al., 2017; Neergaard et al., 2009; Elo & H, K., 2008).

Using the conceptual-analytical model illustrated in Figure 5.4, data analysis was carried out by developing analytical themes. This model includes six themes relevant to the objective of a special education framework that is appropriate for the Indian context. Stakeholders such as special students, teachers, and management were among them. The questions in this study were created to explain special education dimensions such as special students, teachers, technology, management, government, and the economy.

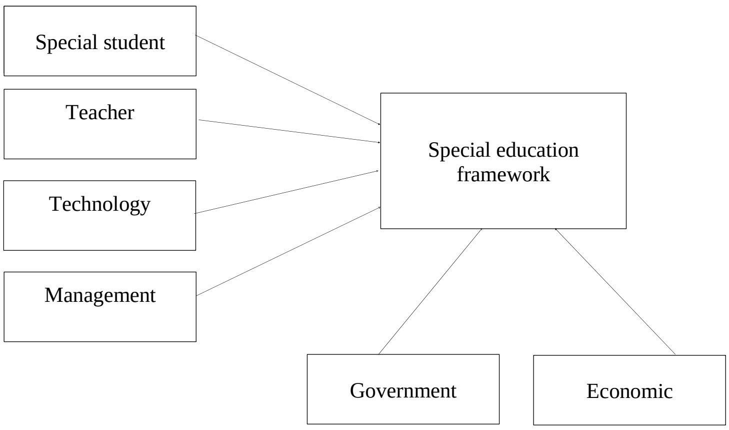


Figure 5.4: Conceptual model for special education

Previous literature and government reports were used to create the interview guide. In addition, modifications were implemented based on the expert's advice, and a final interview guide was developed. The conceptual diagram (Figure 5.4) for special education with dimensions is given above.

5.3.1 Study Design

The interviews were conducted to identify the limitations of special education in the Indian context. In addition, the dimensions like learner, educator, technology, management, government and economy are also measured through the interview. These interviews took place in the Southern part of India, especially in Tamil Nadu and Kerala. The selected special education institutions were involved in this research.

Data collection

Participants

The group was made up of two states in Southern India. All participants who have different disabilities are involved in the interview. In addition, teachers and management are also considered in this study. All kinds of disabled students are interviewed based on six dimensions and various factors. This study focused on special students at the school and graduate level. The in-depth interview was conducted with twenty-three students and sixteen teachers. The research process includes planning, developing interview guidelines/questions, time schedule, conducting the interviews, data interpretation, analysis, results and discussion.

5.3.2 Sample and selection process

Even though India has improved gradually towards inclusive education models, it faces many challenges implementing individual assistive technologies. Therefore, to identify the current status of special education in India, special students and teachers from the southern part of India were invited to participate. This study interviewed a total of 23 students, 16 teachers, and 4 management staff from two different states. The demographic details of the participants are shown in Table 5.5.

Table 5.5: Participant details

Categories	State 1	State 2	Total
Stakeholder unique code			
Special students	S1-S12	S13-S23	23
Teachers	T1-T10	T11-T16	16
Management	M1,M2	M3,M4	4
Age			
Special students			
5-18	6	5	11
18-21	4	4	8
Above 21	3	2	5
Teachers			
25- 35	6	3	9

Above 35	4	3	7
Gender			
Special students			
Male	8	6	14
Female	5	4	9
Teachers			
Male	3	3	6
Female	7	3	10
Education Qualification			
Special students			
School	6	5	11
UG	3	4	7
PG	3	2	5
Teachers			
UG	7	4	11
PG	3	2	5

Sampling

The study locations and sample population were chosen using a purposive sampling technique. The sample population are selected based on the need of the study, and hence purposive sampling method is used to determine the location and participants. The locations were selected based on the presence of a high number of special schools and special students registration.

The total population in the study area of Tamil Nadu (i.e., Chennai and Coimbatore) was chosen because there are more special schools in this area. Moreover, Kerala has been selected for this study because the disabled person literacy rate is high compared to other states in India. Therefore, the special schools in Kerala (i.e., Kannur and Calicut) were chosen to conduct this study. The study elicits stakeholders' attitudes, awareness, and technology usage, including students, teachers, and management staff members.

The head of the special education institutions was conducted through phone and emails to fix the appointment. Then informal meetings were held with the head of institutions. According to their suggestion, the special students and students were chosen. The participants were met personally, and the interviews were fixed. The institutions from various locations (only urban areas) were involved in this study. 23 special students (14 males and 9 females) whose ages ranged from 12 to 32 have participated. The special students with various disabilities are identified to conduct the interview.

The students with six categories of disabilities used selection criteria to analyse mobile-assisted learning in special education institutions. In addition, the teachers (6 men and 10 women) whose ages range from 25 to 56 years were involved in this study. All these teachers taught in special education groups, except two who were the special trainers in the special teacher training institutes.

Table 5.6: List of disability students who participated in the interview.

Disability category	Group 1	Group2	Total
Blindness/low vision	3	2	5
Hearing impairment	2	1	3
Intellectual disabilities	2	2	4
Mental illness	2	2	4
Locomotor	1	3	4
Autism spectrum	2	1	3

These two trainers partly taught in the special education group and partially trained the teacher training students in the regular classes. This study also includes special education trainers as participants. The different types of disabled students who participated in the interview are shown in Table 5.6.

This study was conducted after the approval of the ethics committee in the special education institutions. The details of the participants (both special students and teachers) were anonymous in terms of name, position, and other information.

5.3.3 Interviews

Totally 43 in-depth interviews were conducted in this study. The interview is semi-structured with predetermine issues and openness to new topics that may emerge (Appendix C). The different set of interview questions was prepared for special students, teachers, and management. The predetermined themes for the special students include awareness about the assistive technologies, mobile phone usage, attitude, and economic status of the participants. The new topics include the awareness of mobile apps to assist learning in special education institutions. The determination of the interview questions consists of the attitude of teachers to support students, awareness about assistive technology tools and special training. Additional information about mobile app usage for special education is also added.

Based on the aim of the study, the dimensions and variables are fixed. The first version of the interview questions was framed with a set of dimensions and variables.

i) Special students’ perception of assistive technology tool usage, awareness, and special students' cultural and social background.

ii) Teachers' perception of assistive technology usage, training, and attitude to support special students.

iii) Management perception towards the government schemes and policies, assessment, planning and funding issues.

iv) Government initiations towards policies and schemes and binding laws for special students welfare.

v) Technology development to help the disabled students through ATDs and mobile apps

vi) Economic status of the special student's family and financial support of the institution to develop special education

Five experts in the field of special education validated the draft interview questions, and their suggestions were incorporated in the final version of the interview script. The interview was conducted orally and recorded. Then, it is converted into a written format. The additional details about the usage of mobile as assistive technology in special education are also included. The interviews and discussions are documented for future analysis. Some of the questions asked during the interview process are listed below:

- What are assistive technologies do you use in the teaching-learning process?
- What are mobile platforms/applications used for teaching/learning purposes?
- How are mobile applications/assistive technology influence individuals in various domains such as education, hobbies, and employment?
- Does the continuous usage of digital gadgets cause any problems for the students? Did you get any complaints from the students?
- What are the policies you are following to implement a learning environment for the special students?
- Do you get any complaints about the assistive device used for teaching?
- What are the measures took place to rectify the technical issues?
- What are the technical workshops or training you want to attend?

5.3.4 Data Analysis

A content analysis was conducted using a data-driven process. The primary materials considered in this study are interviewed dialogues with parents of special students, staff and management. The content analysis is mainly used to analyse the qualitative research to identify the overlapping themes. Based on the literature support, the themes were identified and following that, the topics are categorised as a whole, and then overlapping themes are divided into six groups. The themes identified in this study are special technology, learner, government, institution teachers, and economics (Sigstad, 2017). This study aims to capture essential real-time feedback about assistive technologies and mobile apps used in special education. The interview data were further categorised into sub-themes from where it is assembled into themes, as shown in Table 5.7.

Table 5.7: Special education dimensions and factors identified in the study

Authors	Themes	Sub-themes
Abuzaid (2015); Ahmad (2015); Kisbu-Sakarya and Doenyas (2021); Das and Shah (2014); Jha (2002)	Special student	awareness, assistive technology usage, student attitude and belief
Malouf and Schiller (1995); Ashton & Webb (1986); Chu (2011); Ciampa (2017); Kundu et al., (2020); Das and Shah (2014); Bhatnagar and Das (2013); Shah et al., 2014.	Teacher	student supporting attitude and motivation, awareness, and special training
Ciampa (2017); Maor et al. (2011); Khasnabis et al. (2015); Borg et al. (2009); Glueckauf (2005); Bhatnagar and Das (2013)	Technology	assistive technology device usage, mobile gadgets, mobile platforms and apps
Dasgupta (2002); Das and Shah (2014)	Government	binding laws for special educations, schemes and policies, funding
Kundu (2000); Das and Shah (2014); Susan et al. (2015); Das and Shah (2014); Bhatnagar and Das (2013)	Management	availability of assistive technology tools, coordinating systems, assessment, and planning for an assistive device, and funding
Das et al. (2013); Karna (1999)	Economic	parent’s income, financial support

5.3.4.1 Findings

In the study, the participants identified were students (S), teachers (T) and management (M). All the stakeholders belong in the area of special education. They reported that mobile assistive learning has more benefits than other technologies. For instance, one of the respondents phrased it as “*I think the mobile application improves the learning capability than other assistive technology devices*” [T1].

Blindness and low vision

The attitude of the special students to use assistive technology is high compared to the earlier years. The government offers special software for low vision students. The JAWS and NVDA software display spelled words on the screen and encourage the students to learn. This special software is offered freely for the improvement of the students.

"The NVDA software tool used in our institution, which improves students' functionality". [T3]

Assistive technology helped visually impaired students to write the exam in a better way. The special student who does not need the help of volunteers can take the additional time to write the exams. This provision is only possible when there are no volunteers to write the exam. Only one opportunity is given to the special students. They can use either volunteers or additional time to write the exams. These both facilities cannot be used together by the special students.

"There are two provisions available in the regulation; the special students can use the volunteers or additional time to write their exams" [T2, M1].

The special student will describe the answers and explain how to draw the map and diagrams. However, the volunteers will take more time to understand the concept and to write the exam. It will increase the stress and anxiety of the special students during exams. Therefore, to avoid this, the assistive technology/mobile application is recommended by the teachers.

"It will take time for the scribe to understand and write, especially for the maps and diagrams. The development of computer and mobile technology helps me to write exams efficiently. It also reduces stress during exam time "[S1, T1].

The state government will consider social status or family income as a critical factor. Therefore, it provides a proper infrastructure with hostel facilities for special students. In addition, it also arranges employment opportunities for the students.

"Teachers will evaluate the current vision status of the students, and they will submit the report to the IEP team. As per need, the mobile app is developed for the special students" [M1].

The vision assessment test takes place in a classroom setting. It assesses how students use their vision. The strategies for handling the class and developing the mobile app are framed due to the findings. The assessment results are presented to the development team for the Individualised Education Program (IEP). It has determined the extent to which the students require assistance.

Hearing Impairment

Listening and communicating are treated as the main barrier, in which the students especially faced many difficulties maintaining social relations. Sign language and mobile apps help deaf students to communicate through chat. According to the hearing impairment, personalised methods are used in hearing aids.

"Due to hearing impairment, the students are unable to communicate properly to society. The mobile apps help this student interact effectively within and outside the classroom "[T4].

Communication and listening are the main problems for special students. As all the students do not have the same level of skills to understand, the mobile app Sanvaadha is used to bridge this gap in Srilanka. It is a mobile app, which translates pictures and signs symbols into words. This mobile app reduces the burden on special students.

"In the teaching-learning process, the teacher's voice and display the content on the screen. In addition, the language options are available in the app "[M2].

The Rogervoice mobile app is used in the institution to communicate with special students. The teachers and staff use this mobile app and pass the message to the students. Google Live Transcribe and Sound Amplifier are two different types of mobile applications used in hearing impairment. The google live transcribes app will record the voice and display it on the screen.

"These mobile apps also improve the special student communication in the society" [T5]. "It will also encourage us to participate in a group task, and I felt comfortable to communicate with other students in the group" [S4, S8].

Second, the sound amplifier zone app adjusts the sound according to the students' needs. Both these apps are available free of cost. These apps improve the learning capacity of students. Therefore, many institutions use these apps to enhance special student activity inside the classroom.

Intellectual disability

Intellectual functioning not only specifies obtained knowledge and skills but also applying them in a real-time environment. Based on different disability categories, the service is also provided for the students. The various types are classified based on the IQ test, *"During admission time, the IQ level of the special students is identified. In addition, regular assessments are carried out during course time "[T6].*

The instructor reported that,

"The constructive theory is used to validate the special students whereas the instruction theory is used to teach them in special classroom" [T7].

Smartphone apps are used to assist intellectually disabled students. The mobile app "task analysis" provides practical assistance for the student with intellectual disabilities. It also helps them to manage daily activities. The other mobile app, "mean planner," allows them to design and personalise their menus. The input is given as step-by-step instruction for the task, including photos and videos. These apps improve the performance of special students.

"I noticed the dramatic improvement in the performance of tasks once the app was introduced" [T8].

Thus, it positively impacts a mobile app to operate office equipment and other day-to-day activities.

Mental illness:

The mobile app is very useful for bipolar students for self-assessment. This mobile app registers mood swings and provides a solution for that.

"When I felt depressed, I want the guiding device, which conveys that to my family members. Therefore, this mobile app is very useful for me "[S2].

When the students feel depressed, the smartphone app helps to monitor the condition back. It also gives the solution to handle the situation. Meanwhile, this app will also use to send an alert message to family members. The purpose of this app is to perform a self-analysis and provides a solution for mood swings.

Locomotor disability

There are many reasons for this disability include injury, disease, disfigured bones, and muscles. Locomotor disability is common in India.

"Leprosy cured person, but suffering from loss of sensation and paralysis in the eye is studied in the institution. He is facing difficulty in using the assistive device" [M3, T9]

"The special mobile app will help them to improve their performance. The sesame phone enables touch-free access to those students who cannot use their hands" [S5, T9].

"When I said "open sesame", the mobile app starts functioning. It encourages me to use the mobile app for future use" [S6, S3].

According to the student head movement, the cursor is controlled. The items in the mobile app are also selected. Talkitt is another mobile app, which helps locomotor disabled students to speak properly. The maps are also available in the mobile app to assist the special students.

"The ambiguous speech of mine is converted into clear form. It can be able to hear by others through sound recorder" [S7].

Liveware is a computer-based application that the movement of the eyes can control. The cerebral palsy, the benefit for the individual with uncontrolled head movement is tracked by using pupils. Instead of a keyboard and mouse, the eyes are used as a control device.

Autism:

The ASD crashes the nervous system and affects the individual's cognitive, social, emotional, and physical health (Weng et al., 2018). The e-Saadhya introduced a special frame that helps in the improvement of ASD students.

"The framework developed by e-Saadhya for the mentally challenged children would be useful. The mobile app facilitates the parents to upload the voice, image, records various events" [T10, S9].

All the content is provided in the form of multimedia content and videos. This helps special students to understand the content better, learn more quickly, and improve their learning capacity. The institution also arranged many special training programs to improve the technical knowledge of the teachers.

"The special training workshop conducted by CDAC is very useful for us to update the technological" [T12].

"This mobile app also supports the speaking album and visual scheduler, functional reading through 3D object association" [T13].

"*We are using applied behaviour analysis to handle the student who does not respond" [T14]*

The Applied Behaviour Analysis (ABA) is used to analyse the behaviour of students. When a student gives a lack of response, then necessary measures would be taken.

5.3.5 Result

The content analysis is classified into two different types: conceptual analysis and relative analysis. In this study, the conceptual analysis is carried out to analyse the qualitative data. The content of various special education dimensions (learner, teacher, management, technology, government and economic) is chosen, and the analysis is performed to quantify and count its presents. This analysis aims to identify the occurrence of selected terms in the data. Both the explicit and implicit occurrence of the themes are identified and counted. The content analysis themes and sub-themes are categorised and analysed based on the research question and the sample. The result of the content analysis is shown in Table 5.8.

Table 5.8: Content Analysis Result

Category	% of Respondents	Qualitative comments
Technology	23.26%	*"I think the mobile application improves the learning capability than other assistive technology devices."*
Learner	6.98%	*"When I said "open sesame", the mobile app starts functioning. It encourages me to use the mobile app for future use."*
Government	18.60%	*"Funds are not sufficient for the students in our institutions. Therefore the government have to introduce many policies and schemes to encourage special students."*
Institution	11.63%	*"The constructive theory is used to validate the special students whereas the instruction theory is used to teach them in a special classroom.*
Teacher	9.30%	*"The special training workshop conducted by CDAC is very useful for updating the technical knowledge, and we prefer more work to attend. Moreover, we have professional contact with the teachers from other institutions, which will help organise the special education system better."*
Economic	30.23%	*"Due to my economic situation, I am unable to spend more money on my child education. If I get any help from the government or some organisation, that it would be helpful for my family."*

In this study, the economic factor (30.23%) is identified as one of the essential factors in the special education framework. The stakeholder's special students, teachers and management, emphasise that the lack of funding is the barrier and cause for the failure of many schemes and policies. Moreover, the economic status of the special students is below the poverty line, so that they are unable to use the facilities and technologies available for them. Next to the economic factor, the technology scores 23.26% because many special students are aware of the ATDs and use them in their daily needs. Many institutions use ATDs to deliver their instruction to special need students. This study confirmed that ATDs also improve students' attitude and behaviour in the classroom and society. In addition, it is also identified that the ATDs are more costly and difficult to operate the special students falls under tire-3. Therefore, this study suggests mobile apps as an alternate solution for the difficulties faced by special students. Hence, the awareness and usage of the mobile app among the stakeholders are identified through the content analysis. The next factor, government (18.60%), plays a vital role in special education because the policymakers introduce many special student welfare schemes and policies. The Government of India launches many projects and policies to develop the livelihood of the special students.

Many governments approved institutes and NGOs are offering special education all over the country. Most of the institutions are suffered from financial crises because of the population of disabled students. In India, the disability population is more compared to previous years. 2.68 crore people are disabled out of a total population of 121 crores, indicating that 2.21 per cent of the population is affected by one or more disabilities. Therefore, management theme scores (11.63%) through content analysis. The teachers (11.63%) and special students (6.98%) factor scores low compared to other themes because the contribution of these themes to set up the special education system is less. The teachers and special students are considered as users to utilise these ADTS and other technologies. Even though special students and teachers are considered important, teachers and students' role is relatively less than other themes in the special education system. Hence the content analysis also shows the same result in this study.

5.4 Study 7: Mobile assist civic and e-learning service (Sentiment Analysis)

5.4.1 Data collection

The main intention of this research is to measure the users' emotions towards e-learning services in the mobile platform. Six different emotions like anger, disgust, fear, joy, sadness and surprise are analysed in sentiment analysis (Ekman, 1992; D'Avanzo et al., 2017). In addition, the polarity values like positive, negative and neutral are also identified in this study (Liu et al., 2008).

UMANG related tweets were collected from the Twitter database. Both civic learning and e-learning apps related tweets were also collected in this study. The Twitter database has been chosen in this study because users often use Twitter to show their emotions (Statista.com, 2019). Social media is considered a powerful platform to reflect the users' emotions for real-time scenarios. Martinez-Rojas et al. (2018) also suggested that Twitter is a better social media platform to provide feedback about all domains, especially education-related tweets shared as a daily routine. The different hashtags are used to collect the tweets from the Twitter database are shown in Table 5.9.

Table 5.9: Hashtags used in this study

Categories	Mobile apps	Hashtags
Civic learning app	cVIGIL	#cVIGIL OR #VoterAwareness OR #LokSabhaElections2019 OR #DeshKaMahaTyohar OR #elecquiz OR #ceoup
	Divyang Sarathi	#Divyang Sarathi OR #Department of Empowerment of Persons with Disabilities OR #Universal Access and the provisions of the Rights of Persons with Disabilities Act 2016 OR #UNCRPD
	Agrimarket	#AccessibleIndiaCampaignMobile OR #AgriMarket OR #DigitalIndia OR #DigitalIndiaEssentials OR #AccessibleIndiaCampaignMobile
e-learning app	SWAYAM	#SWAYAM OR# SWAYAMPrabha OR #SWAYAM OR #SWAYAMPrabha OR #TransformingEducation OR #TransformingIndia OR #NewIndia OR #SabkoSikshaAcchiSiksha OR #qualityeducation
	ePathshala	#SchoolEducation #NCERT #CBSE #ePathshala #GSEB OR #e-pathshala OR #ePathshala OR DigitalIndAward OR #goDigital OR #digital OR #MobileApp OR #webapp OR #Institutional OR #attendance OR #homework OR #Exam OR #results OR #fees
	E-CBSE	#E-CBSE OR #cbseclassXIIresults2019 OR #DigitalIndia

Many users like Twitter because of its “concise and expressive nature” (Kumar et al., 2020; Wu & Shen, 2015). Most of these applications were widely mentioned in the news during the election period, as per the current study done in April 2019. More than thirty thousand tweets were collected related to civic and e-learning mobile apps.

Data pre-processing

The Twitter database is used to predict the election results based on user opinion (Ennaji et al., 2019). The Twitter Application Program Interface (API) extracts the tweets from the social media platform (Jeong et al., 2019). The Twitter dataset was chosen as each tweet approximately consists of 0.47 emotion tokens (Suresh & Raj, 2017; Liu & Zhang, 2012). These emotion tokens reflect the users’ feedback on the social media platform (Jamali et al., 2019).

In this study, the rule-based approach was chosen to categorise the tweets based on emotions (Okeyo et al., 2018). The data extraction process was carried out in four steps. In step 1, tweets were extracted from the Twitter database with the help of hashtags (Chang et al., 2019). In step 2, tweets were cleaned to remove the duplicate entries from the input dataset (Pang et al., 2002; Pang & Lee, 2008). The data cleaning was also done manually to remove typographical errors (Van den Broeck et al., 2005). In step 3, the rule-based approach was utilised to classified the tweets based on positive, negative and neutral words (Yang et al., 2019). Meanwhile, the tweets were classified based on NRC emotion tokens (Taboada et al., 2011; Kušen & Strembeck, 2018). Finally, in step 4, the results obtained from step 3 were aggregated based on emotion tokens and the final result was achieved.

In this study, tweets related to civic and e-learning services were pre-processed. The awareness of the digital e-services was analysed and compared using Twitter sentiment analysis. cVIGIL, Divyang Sarathi, Agrimarket, SWAYAM, ePathshala, and E-CBSE hashtags collected civic and e-learning related tweets. The present study has chosen these mobile apps because the Indian government introduced these e-services under the National e-Governance Plan. These mobile apps were launched simultaneously, and an updated version was introduced at the same period. More than thirty thousand tweets were analysed in this study. The maximum of five thousand plus tweets for cVIGIL and a minimum of eight hundred plus tweets for Divyang Sarathi were extracted.

The data were collected between seven-day time intervals in April 2019. Tweets were collected weekly for one month and were collected in the form of unofficial instructions. In the first phase, appropriate keywords or hashtags related to the mobile apps were collected. Then, using R–script, the tweets were extracted from the Twitter database. Therefore, those tweets were pre-processed using R-script and converted into n-grams (Rathore & Ilavarasan, 2020).

5.4.2 Data Analysis

In the data analysis phase, the users' emotions were explored from the tweets. The user sentiments were measured in two aspects, polarity and emotions (Zhang et al., 2019). Based on sentiment analysis, the user awareness levels were compared. Emotions help to identify the outreach of the ICTs among citizens in India. It also shows that the awareness of e-service increased the usage of digital resources. Twitter positive emotions encouraged other users to use the mobile-assisted e-service for their daily activities. It will also spread the necessity of e-service among mobile users through social media platforms (Goh et al., 2013). The positive and negative emotions were again classified into different labels (Giachanou et al., 2019).

Out of thirty thousand plus tweets, the percentage of positive and negative tweets of each e-service is analysed. As a result, the majority of the tweets shows positive polarity. In civic learning mobile apps, 91.27% positive tweets were expressed for Divyang Sarathi, 7.84% for cVIGIL and 3.78% for Agrimarket. The percentage of positive and negative emotions in the tweets were measured in this study and shown in Figure 5.5.

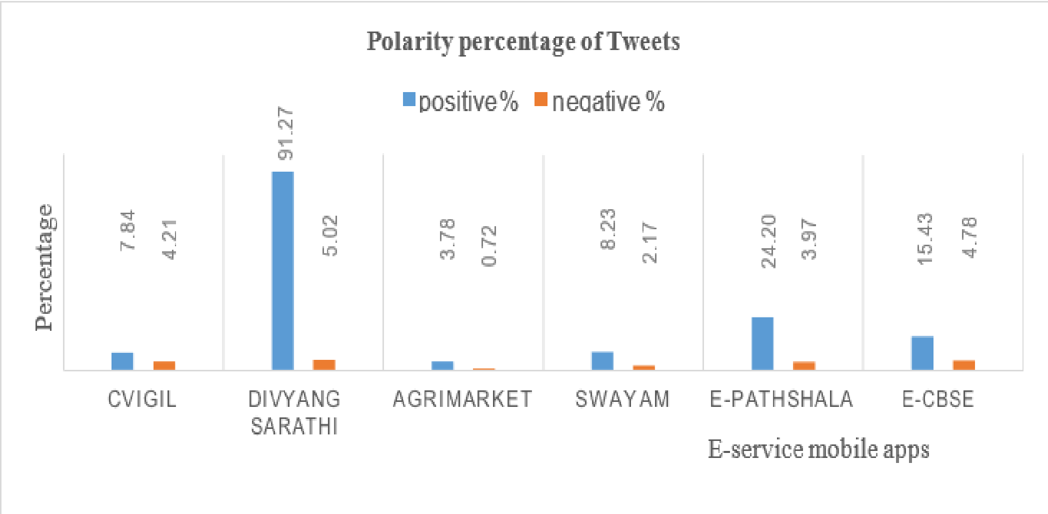


Figure 5.5: Polarity percentage of Tweets

The users have more awareness of e-learning apps, specifically 24.20% in ePathshala, 15.43% in E-CBSE and 8.23% in SWAYAM. The result shows that the awareness of the mobile e-learning app is more compared to civic learning.

Polarity and emotions

The polarity can be measured as positive, negative and neutral based on tweets. In this study, the sentence selection method is used to classify emotions. The sentiment classifiers are analysed using machine learning algorithms (Washha et al., 2019). Using these algorithms, the sentiment scores were assigned for each token separately. On the other hand, the lexicon directories were used to classify the tweets based on polarity. Because the tweets are a mixture of emotions with special characters in the instruction format, this study combines these two approaches to perform Twitter sentiment analysis (Agarwal et al., 2011).

In the first phase, the Naive Bayes' classifier filters the tweets based on polarity. The naive Bayes' classifier uses four steps. In step 1, it built the vocabularies, and then it matches the tweets against the vocabularies and based on these, the polarities are identified. In step 2, the test set is prepared as an input file. In step 3, the test set is converted into emotion tokens. The package "Syuzhet" in the R tool is used to perform

NRC emotion lexicons, which converts the tweets into NRC emotion lexicons (Mohammad & Turney, 2013). Finally, in step 4, the polarity and emotion labels are classified based on tokens.

5.4.3 Result Analysis

The present study evaluates the awareness level of users about the civic and e-learning service in the mobile platform. Our result shows that the awareness level of civic learning is less compared to the e-learning service. This result is matched with the previous studies conducted in the Indian context (Saxena, 2018). We have tested the awareness level of the users through sentiment analysis. Two different domains were selected, and three different types of mobile apps were tested under each category.

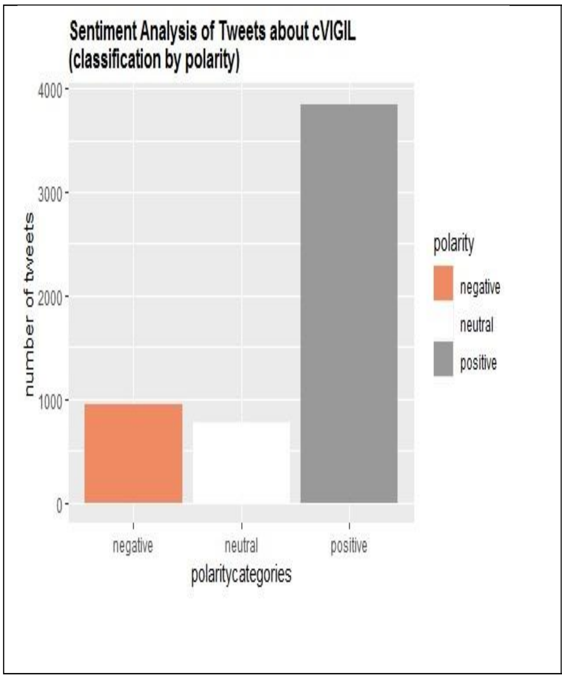
Civic learning apps

Civic learning is how young people develop their knowledge and skills by interacting with others in society. Under the Civics Learning Act 2021, the American History and Civics Education National Act (AHC-NA) promotes civics learning among schools and higher education institutions. In addition, grants are provided for the students and teachers to encourage their e-service learning and community service projects (Civics Learning Act, 2021). Similarly, the government of India takes initiatives to enrich civic understanding among Indian citizens under the UMANG schemes.

cVIGIL

The cVIGIL m-learning app scored more positive polarity during analysis. It indicates the high awareness level of citizens about the election proceedings. The number of users using this app increase the positive feedback. This shows that the civic learning and awareness of the citizens is more because of mobile apps. This app is user-friendly and easy to operate by users so that many users download this app through Android and iPhone. Figures 5.6a and 5.6b show the cVIGIL awareness level of the citizens based on polarities and emotions.

Our result shows that the positive polarity scores for cVIGIL were more than the others, indicating that users are aware and satisfied with the civic learning app. The positive emotion “joy” has more scores compared to other emotions. It suggests that the users are happy with the cVIGIL mobile app. Thus, the perception of users about this mobile app is concluded as positive.



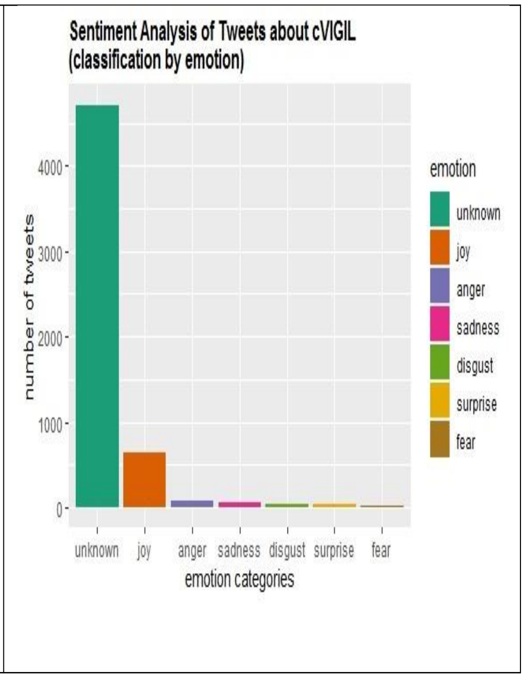
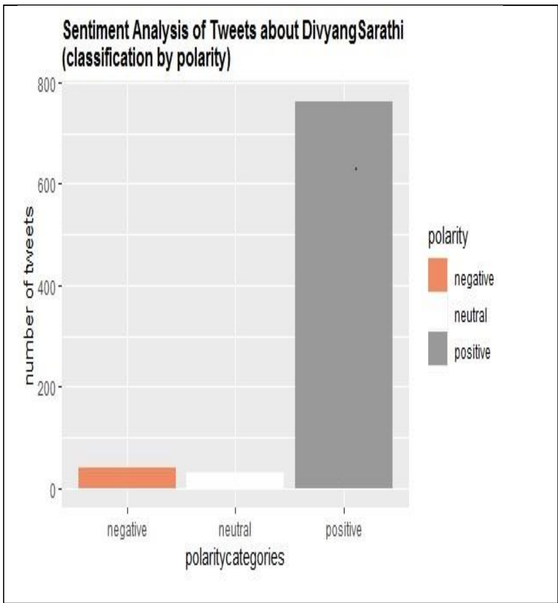


Figure 5.6a: cVIGIL polarity analysis

Figure 5.6b cVIGIL sentiment analysis

Divyang Sarathi

The total number of tweets collected for Divyang Sarathi was more than 800 within one month. It shows that the awareness of this mobile app is comparatively less than other apps. Figures 5.7a and 5.7b show the Divyang Sarathi awareness based on polarities and emotions.



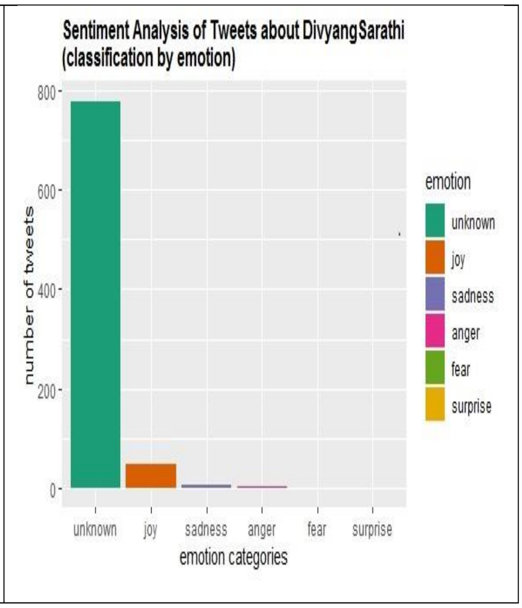


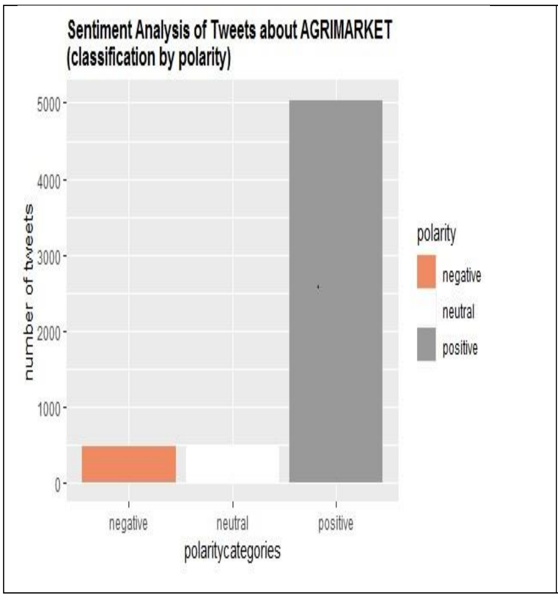
Figure: 5.7a Divyang Sarathi polarity analysis

Figure: 5.7b Divyang Sarathi sentiment analysis

The result shows that positive polarity and “joy” scored more than the other polarities and emotions, respectively. This app is discussed less in the social media platform compared to other apps chosen for this study. The above results show that the awareness about the Divyang Sarathi mobile app is low. To create awareness, the government often needs to take necessary steps to advertise this app among special needs people.

Agrimarket

The total number of positive tweets collected for this mobile app was more. The positive polarity scores were more than negative and neutral. It indicates the farmers have more awareness and are satisfied with this mobile app. Agrimarket awareness based on polarities and emotions is shown in Figures 5.8a and 5.8b.



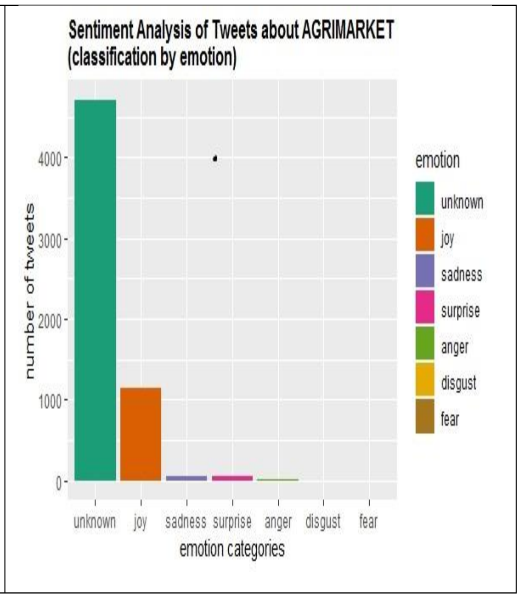


Figure: 5.8a Agrimarket polarity analysis

Figure: 5.8b Agrimarket sentiment analysis

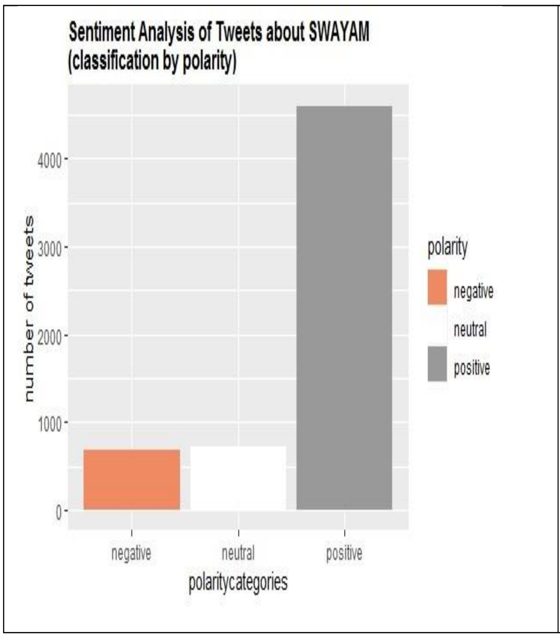
Our result shows that the emotion "joy" is more compared to others. Moreover, it shows that the outreach of the Agrimarket is more. Among civic learning e-service, the Agrimarket mobile app scores more compared to cVIGIL and Divyang Sarathi m-learning.

E-learning mobile app

The Government of India promotes e-learning mobile apps for the improvement of education sector. The main aim of these m-learning apps is to bridge the digital divide among rural and urban areas. Three different e-learning mobile apps were selected under each category and were analysed.

SWAYAM

The sentiment analysis result shows that the user's expectations are achieved through SWAYAM mobile app. The awareness of this app is more because most of the higher education students use this e-learning mobile app. The higher education institutions are also promoting this app to their students as an additional academic resource. The reach of this mobile app is high because most of the mobile users fall under the student categories. The higher education students are also familiar with other online environments, such as Coursera and edX. Therefore, the students show more interest to use this mobile app.



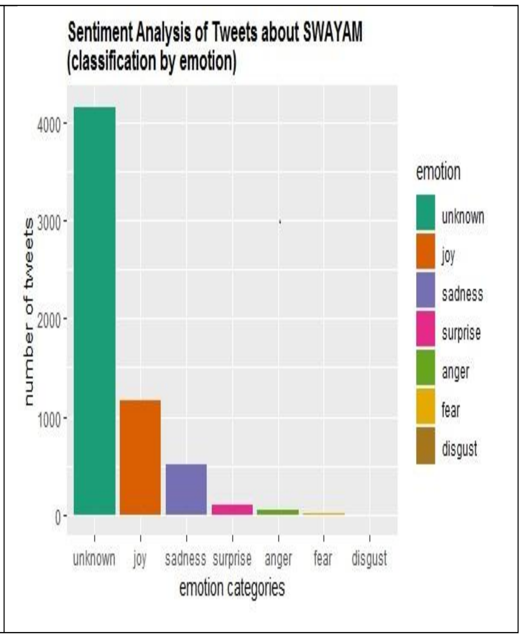


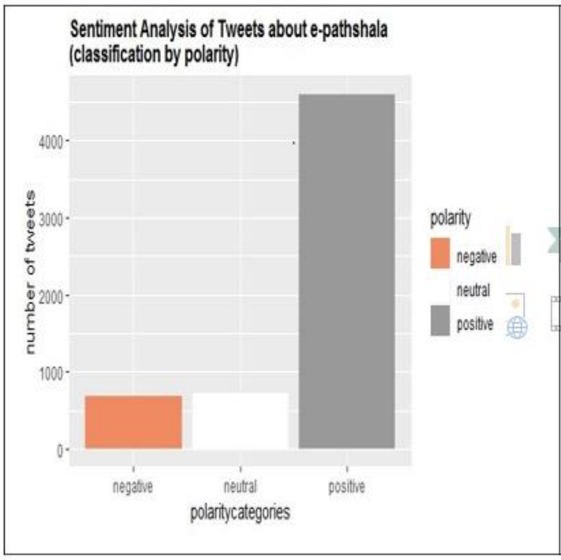
Figure 5.9a: SWAYAM polarity analysis **Figure 5.9b:** SWAYAM sentiment analysis

The user's emotion 'joy' scores are higher than the other emotions. It shows that the positive polarity of the user is more compared to other polarities. It is because the students have prior knowledge about the e-learning platform. Therefore, many students used this e-learning mobile app to learn online courses. The sentiment analysis of the SWAYAM m-learning app with polarities and emotions is shown in Figures 5.9a and 5.9b.

e-Pathshala

e-Pathshala provides particular services for students, teachers, and educators. For the student, it allows access to the digital textbook and e-Resources. Because of the user-friendliness of the service, the awareness level about this mobile app is high. The positive feedback about this app is more compared to other mobile apps.

Our result shows that the positive polarity and emotion "joy" is more for the e-Pathshala m-learning service. It shows that the outreach of the mobile app is high compared to other e-services. The sentiment analysis of the e-Pathshala m-learning app with polarities and emotions is shown in Figures 5.10a and 5.10b.



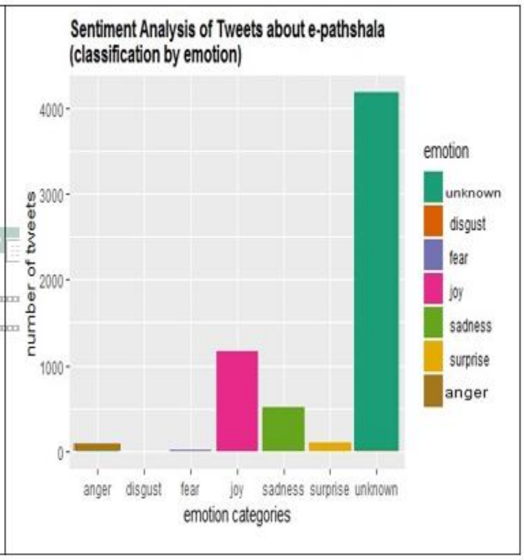
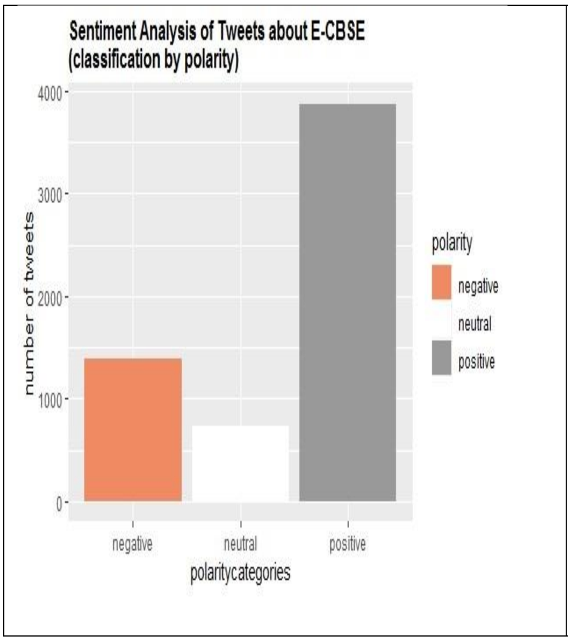


Figure: 5.10a e-Pathshala polarity analysis

Figure: 5.10b e-Pathshala sentiment analysis

E-CBSE

E-CBSE mobile app provides e-learning materials for school students and teachers. It also offers high-speed Internet and digital infrastructure service, which increased the digital literacy rate through this mobile app. The positive polarity of this app is high compared to others polarities. It shows that the students are active participants in this m-learning app. The Indian government has conducted many awareness programs among school students to spread the benefit of this app. Therefore, the reach of this app is more in secondary schools.



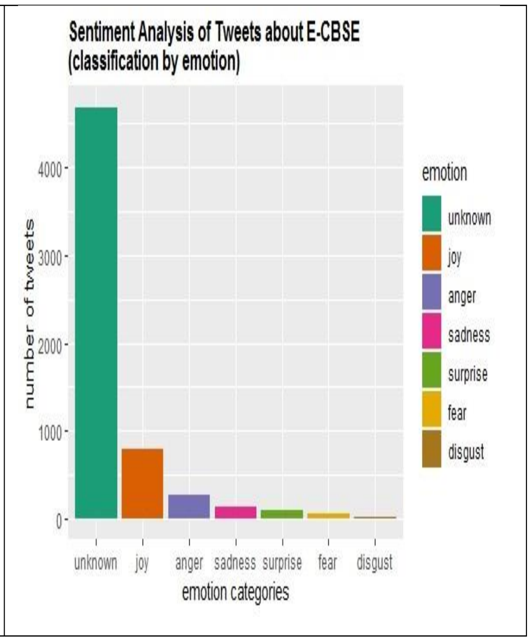


Figure 5.11a: E-CBSE polarity analysis

Figure 5.11b: E-CBSE sentiment analysis

The result shows that the emotion "joy" is more compared to other emotions. It indicates that the awareness of the mobile app E-CBSE is more among school students. The output of sentiment analysis with polarities and emotions are shown in Figures 5.11a and 5.11b.

5.4.4 Performance Measure

Overall performance of the model is analysed using two approaches: a) chi-square test b) *Naive Bayes approach.* The chi-square test is used to measure dependency between two quantitative variables. At the same time, the Naive Bayes algorithm is a technique used to construct classifiers. It is based on Baye's theorem and used to handle high dimensional data (Song et al., 2017; Jianqiang & Xiaolin, 2017).

5.4.4.1 Performance Measure using chi-square test

The chi-square test or "goodness of fit" statistic compares the observed values to the expected values in the data set (Khan et al., 2014). It also identifies the difference between two frequencies (observed and expected) and represents the result in a contingency table. Each row consists of one categorical variable in this table, and each column contains another categorical variable (Go et al., 2009; Singh et al., 2017). The chi-square value is computed using the formulas,

$$\chi^2 = \Sigma\,\Sigma\,(f_{ij}-E_{ij})^2/Eij \quad \text{-----------------} \ (1)$$

$$i=1,2 \ j=1,2\ldots$$

where f_{ij} represents the indicator frequency in positive or negative tweet sets.

E_{ij} represents the expected frequency of i and j.

The expected frequency is calculated by using the formula,

$$E_{ij} = \text{row total}_i * \text{column total}_j \ /\text{total number of observation} \ \text{---------} \ (2)$$

The user awareness about m-learning apps (civic and e-learning apps) is analysed via the chi-square test. Based on the literature support, the hypothesis is framed as,

H_1: Assuming there is an association between Twitter frequency and m-learning apps awareness among users.

To accept the hypothesis, the significant value of p should be less than 0.05 ($p<0.05$). Our finding shows the χ^2 value is 371.121 and the value of p=0.00, and the result is significant at $p < 0.05$ (Wang et al., 2018); therefore, the hypothesis is accepted. The chi-square test confirms that the tweets are associated with m-learning apps' awareness among users. Hence, this study confirms that the mobile apps' awareness level is high among

Indian users through Twitter sentiment analysis. According to a Statista (2019) report, the total number of mobile phone users increased to 420.7 billion in India, and 79% of students use smartphones as the primary mode of online learning (Statista, 2021). Hence, the Statista report also supports the result of this study.

5.4.4.2 Performance Measure using Naive Bayes approach

In this study, the Naive Bayes method predicts the overall sentiment of m-learning apps in the Indian context. With the help of the RapidMiner software tool, the performance measure of the model is analysed (Arunadevi et al., 2018). As a result of the Naive Bayes algorithm, the confusion matrix is created. The confusion matrix summarises the performance of the classification model. It consists of two classes (actual and predicted class) and four parameters (true positive, true negative, false positive and false negative). The true positive (tp) has correctly predicted values in both actual and predicted classes. At the same time, the true negative (tn) consists of correctly predicted negative values in both categories. On the other hand, the false positive(fp) and false negative (fn) are represented in the contradicted values in both classes (Jianqiang & Xiaolin, 2017). Based on these four parameters, the precision and recall values are calculated as,

Precision = tp/tp+fp --------------------------- (1)

Recall = tp/tp+tn ---------------------------- (2)

The precision values are correctly predicted positive values observed out of total positive observations (Ismail et al., 2018). The recall values are calculated based on the ratio of correctly predicted observations to the total observations (Saif et al., 2016). Finally, the accuracy of the model is estimated using the following equation,

Accuracy = tp+tn/tp+tn+fp+fn ---------------- (3)

The accuracy shows the correctly predicted positive observation ratio to the total observations (Panasyuk et al., 2015). The result generated by the Naive Bayes approach is shown in Table 5.10.

Table 5.10: Naive Bayes Production Model Result

Class precision		Class recall		Accuracy
pred.positive	81.72%	true.positive	99.64%	81.42%
pred. negative	59.09%	true.negative	7.14%	

In our model, the precision rate is 81.72% (pred. positive) and 59.09% (pred. negative), and the recall value is 99.64% (true positive) and 7.14% (true negative). Therefore, the accuracy of the model using the Naive Bayes approach is estimated as 81.42%.

5.4.5 Findings

The findings clearly explain the awareness level of users about e-service in the m-learning platform. Mobile phone usage is identified as the main reason for the growth of e-service (Sakibayev et al., 2019). In India, the Internet penetration rate plays a major role in the development of mobile apps. Therefore, this study confirms that mobile phones' reachability promotes m-learning among users in India. The tweets were extracted from the Twitter database, and the users' opinions were analysed in various domains such as election, agriculture, and special education (Qazi et al., 2017). On the other hand, the e-learning service in higher education and school level were also analysed. Finally, the emotions of users regarding the civic learning apps were compared with the e-learning apps.

Our study result shows that the users have more awareness of e-learning services compared to civic learning. It is because half of the population who use mobile phones falls under the youth categories. Many higher education students and school students use mobile apps for their daily activities (Thakur and Srivastava, 2013).

The usage of the election app is more, but the active time is less compared to other apps. This is because the cVIGIL app is functional only during election time, and its usage is limited to a specific period (ECI, 2019). Kiyohara et al. (2018) explored how smartphones penetrated into the election process and campaign in South Korea. As a result, the authors confirmed that civics learning helps people understand democratic values, especially in election time. It also enhances people's knowledge about their citizenship and improves the relationship between political parties and voters in developing countries.

Kukulska-Hulme and Shield (2008) stated that the mobile platform is a mediator to promote e-service anywhere anytime. Therefore, the research team at the University of Granada, and the University of Murcia, Spain, used iPad and iPod devices to promote e-service to the special students (Fernandez-Lopez et al., 2013). As a result, the special students are satisfied with the mobile apps that are easy to download through play store (Ismaili, 2017). In India, Divyang Sarathi mobile app is helpful for specific group of users with special needs. Therefore, the usage of this mobile app is limited to a special community. Our result shows that the awareness of this app is less compared to other civic apps. The two main drawbacks of this app identified in this study are lack of understanding and the limited number of users.

The agricultural mobile app could provide information about the markets, services and connect farmers with customers. For example, in Germany, farm management software named “AGRO-NET” is used to reduce the complexity of the farmers (Steinberger et al., 2009). Similarly, in Greece, the Bio@gro m-learning app provides information related to agriculture practices, government services, markets, and increasing farmers’ revenue (Prasad et al., 2013). Likewise, the F-Track Live farm management app enhance the agriculture-related mobile service to the Australian farmers. Many past studies also confirmed that the growth of mobile agricultural app is significantly high in developed countries like Sweden, Kenya, Australia and developing countries like India and other European countries, including Uganda, Tanzania (Steinberger et al., 2009; Prasad et al., 2013).

Similarly, in India, the agriculture-related app Agrimarket is introduced along with the agriculture insurance app. The farmers who are familiar with the mobile app gets the full benefit of this app. The mobile app’s integration with the agriculture management system has a positive impact on agriculture. It brings in a revolution in Indian agriculture while also increasing the revenue of the farmers (Inwood & Dale, 2019). The farmers in India are more aware of and use this agriculture app.

The usage of e-learning mobile apps is more among student communities, including school and higher education students. The main intention to introduce mobile apps is to bridge India’s digital divide (Waheed et al., 2016). When e-learning is provided through other platforms, the infrastructure is considered as a major challenge. To overcome this challenge, e-learning services are promoted through mobile platforms (Sakibayev et al., 2019; Jampala & Shivnani, 2019). Many developing countries create m-learning programmes that are suitable to the specific needs of their students. To meet the needs of students in Taiwan, teachers primarily focus on technical issues and content quality (Lai et al., 2016).

Many e-learning contents are developed and promoted through mobile platforms in India as well. SWAYAM is one of the most popular online platforms that provide courses through videos and text format. The users show more interest in the online courses because they are already familiar with the MOOCs platform like Coursera, edX (Gupta and Jain, 2017; Gupta, 2019; Pujar & Tadasad, 2016). Apart from this, the digital initiative schemes and promotions about the e-learning service quickly reached the student community through mobile platforms. Therefore, the reach of SWAYAM is high among the student community. The same result is reflected in the sentiment analysis.

In Ghana, an m-learning app called iREAD was developed to improve the childrens’ literacy for school students in grades 1, 2, and 3. E-books were provided in the form of storybooks to encourage the reading activities of the students. This mobile app will help overcome limitations such as the lack of human and other material resources across geographical distances (Oakley & Imtinan, 2018). Similarly, in India, the ePathshala app provides a digital textbook for students. The e-content of this mobile app has more content quality and attracts many users to use this app. As a result, many users are satisfied with the e-content, and the same effect is reflected in the sentiment analysis (Balaji & Kuppusamy, 2016). Therefore, the usage of ePathshala is comparatively higher than the other two education-related applications.

In Egypt, the m-learning app is designed based on the content quality service. It provides up-to-date content to the school students along with quizzes and exams. Adel Ali and Rafie Mohd Arshad (2018) confirmed that students' performance has increased after using m-learning apps in academics. On the other hand, in India, E-CBSE is a special mobile app for school students and it provides e-content for the students from 1 to 10 standards (National Council of Educational Research and Training, 2019). As a result, many Indian schools recommended this app to their students and promoted awareness about the usage of this mobile app.

The above result shows that the usage of mobile apps is more in India. The chi-square test confirms through Twitter analysis that the awareness of m-learning apps is high. In addition, accuracy of the overall model is estimated through the Naive Bayes approach. The AppsFlyer report (2018) also supported the same result and reported that India is the number one country to install mobile apps and use them per month. Overall, 12.1 million mobile apps were downloaded by Indian users in 2018 (Natanson, 2021). Because of the above reasons, India creates the fastest developing mobile app market in the world. It is one of the primary reasons to conduct this study in the Indian context.

A comparison of civic and e-learning mobile apps was performed, and results were discussed. It is identified that online users have more awareness about e-learning mobile apps than civic learning apps. Even though smartphone usage is more, the use of civic learning is comparatively less among Indian users. Therefore, to create awareness, the government should initiate some digital campaigns from the National e-Governance plan.

Advertisements should be given through media like newspapers, televisions other than social media. It will create awareness among citizens in rural areas. It also seeks the attention of the ordinary person in society. Thus, it helps them to know the roles and responsibilities of the citizens in the country. The feedback from the online platform should be considered for the future development of mobile apps. It will help to maintain and improve the constitutional democracy in India. The awareness about civic learning will improve the social and emotional thinking of the users. It also encourages a sense of unity and cohesion in society. This study concluded that civic and e-learning services promote awareness about technology usage and educate citizens about their roles and responsibilities.

This study aims to measure awareness levels of the citizen towards e-service in the Indian context. Two different categories of e-service: civic and education-related services, were considered for the analysis. First, tweets related to general e-services such as cVIGIL, Divyang Sarathi, and Agrimarket were extracted using hashtags in the Twitter database. Second, we collected tweets about educational services like SWAYAM, e-pathshala, and E-CBSE. The maximum number of tweets searched in each category was 6000. Third, both the user awareness and emotions were analysed using Twitter sentiment analysis. Overall, the awareness level for the general e-service is less compared to the education-related e-service.

5.4.6 Discussion

This study compared the usage of mobile apps in civic learning and e-learning service. It is identified that the user perception towards m-learning service in civic learning is less compared to e-learning. Even though mobile devices are widely spread in developing countries like India, the usage of civic learning is less. The reason was found through Twitter sentiment analysis. The awareness level of the users towards e-learning is more. It is because the government initiated many awareness programs through the digital India campaign. UMANG scheme has an excellent reach to the students compared to the public.

As evidence, many online users discussed their opinion about mobile apps on a social media platform like Twitter. There were many positive tweets found related to mobile e-learning apps. Overall, the e-Pathshala mobile app has a more favourable score compared to other apps. For e-pathshala, the high-quality curriculum-based interactive e-content is developed by experts from Indian universities. It also provides various modules for different subjects across all disciplines. Therefore, this study concludes that the users have more awareness about e-Pathshala than all other service categories. Overall, the users' awareness of the e-learning mobile apps is more than civic learning apps in the Indian context.

This study collected the feedback of online users regarding different types of mobile apps. The polarities and emotions were identified in this study which will help the app developers to improve mobile applications. In addition, this study helps to find out the requirement of the citizens based on emotions. This study is also helpful for the government policymakers to introduce new schemes and policies to guide citizens better. Thus, the conclusion of this study would support the policymakers to develop mobile apps to fulfil the government's intention and attract citizens towards technological revolution. This study includes only limited mobile apps, and more apps could be considered for future research.

5.5 Conclusion

The purpose of this study is to improve e-learning adoption in the Indian context. Thus, this study uses qualitative research to analyse the mobile-assist e-learning service in two different case studies. First, the qualitative interviews are conducted in the special school to analyse the benefits of mobile apps over ATDs. This research involves: i) interview guidelines are prepared with the help of literature support and expert suggestion ii) identifies the respondents in the special schools, including special students, teachers and management iii) content analysis is performed to analyse the qualitative data iv) the traditional ATDs are compared with the mobile apps suitable for all disabilities v) suitable theoretical framework is proposed. Second, the Twitter Sentiment Analysis was performed on the secondary Twitter dataset. This research involves: i) based on the literature support the keywords are identified ii) using hashtags the Tweets are collected from the Twitter database iii) the data are pre-processed and analysed using R tool iv) the polarities and emotions of the tweets are extracted v) the civic and e-learning mobile app awareness levels are compared vii) the suggestions are given to improve the service of m-learning apps. The qualitative analysis mainly focuses on the mobile platforms through which e-learning is promoted to the end-users.

CHAPTER 6

SYNTHESIS, IMPLICATIONS, AND RECOMMENDATIONS

Chapter 6

Synthesis, Implication and Recommendations

6.1 Introduction

The structure of this chapter is as follows. The synthesis of findings from qualitative and quantitative study methodologies is presented in Section 6.2. The study's implications are discussed in Section 6.3.

6.2 Synthesis of the Study

As mentioned in Chapter 3, the research synthesis could be discussed in light of the quantitative (questionnaire survey) and quantitative interviews and secondary data) study methodologies. The synthesis of findings from the study techniques described in chapters 4 and 5 is discussed in this section. E-learning adoption factors, gender-based e-learning, e-learning barrier factors, and cloud analyst have been studied in subsection 6.2.1. In subsection 6.2.2, the barriers to e-learning are discussed and the benefits of mobile applications in special education and the awareness of mobile apps among Indian citizens. In terms of triangulation of studies and potential ways to improve it, subsection 6.2.2 integrates qualitative and quantitative analysis outcomes.

6.2.1 Understanding and Modeling Variables

Statistical analysis was used in the quantitative study to identify the various dimensions of the e-learning framework. The factors influencing e-learning adoption, gender-based e-learning factors based on chosen country studies, and e-learning barrier factors that affect e-learning adoption are all examined as part of this study. As a result of the two separate study approaches, the suitable platform to promote e-learning was attempted to be studied. As a result, the mobile platform is analysed from the end-user's perspective, and cloud-based e-learning is examined from the viewpoint of management. In addition, a pedagogical dimension is included in the audience analysis to identify the opinions of various types of users, such as higher education students, online users, and special school students.

Recall that quantitative data was utilised to identify the various dimensions, including technology, learners, design, and barrier dimension. Under the technology, learner and design dimensions, various e-learning adoption factors such as system characteristics, technological awareness, learner characteristics, perceived usefulness, and perceived satisfaction were found. Select country studies also identified factors influencing gender-based e-learning, such as user attitude, user behaviour, technology awareness, and perceived satisfaction. Various factors such as a lack of ICTs, a lack of Internet, discomfort in ICT use, user anxiety, a lack of digital literacy, and a lack of prior knowledge were identified under the e-learning barrier dimension. A survey questionnaire was used to collect data for the statistical analysis from higher education students. Based on literature support and quantitative analytic findings, it is confirmed that the infrastructure plays a vital role in e-learning adoption. As a result, the cloud-based e-learning system is deployed, and the infrastructure as a service is evaluated using CloudAnalyst, a cloud simulator. Thus, cloud-based e-learning is analysed under the management dimension.

The discussion of quantitative components obtained from empirical studies represents the relationship between different dimensions and factors in the e-learning framework. The system characteristics, learner characteristics, e-learning barriers and e-learning platforms were identified on e-learning adoption in the Indian context. As a result, it would be useful if future research could use these models to investigate the significance of the variables and their relationships on e-learning adoption.

According to earlier studies, India faces e-learning challenges in implementation. As a result, the study takes into consideration empirical research on e-learning influencing factors, gender-based e-learning, e-learning barriers, and cloud-based e-learning. As a result, the study examines a cloud-based e-learning system to improve infrastructure facilities from a management perspective. However, some common variables and practises that these studies might highlight, as shown in Table 6.1.

The study reveals more common variables through quantitative data analysis in Table 6.1, which were considered and studied in four different situations based on their combination.

Table 6.1: Common Variables identified in this study

Variables	E-learning adoption influencing factors	Gender-based e-learning	E-learning barrier	Cloud-based e-learning
System quality	✓			
Information quality	✓			
Service quality	✓			
Collaboration quality	✓			
Computer-self-efficacy	✓	✓		
Internet-self-efficacy	✓	✓		
Learner attitude	✓	✓		
Learner behaviour	✓	✓		
User confidence				
Prior knowledge	✓		✓	
Perceived usefulness	✓	✓		
Perceived satisfaction	✓	✓		
Infrastructure			✓	✓
Internet			✓	✓
User anxiety			✓	
Lack of digital awareness			✓	

Case 1: Factors influence e-learning adoption

Based on the quantitative research findings, certain variables influence system characteristics and learner characteristics on e-learning adoption.

- *System characteristics*: The system characteristic is one of the critical factors influencing e-learning adoption. The study revealed that higher education students do not feel satisfied with existing e-learning performance because of the system quality.
- *Learner characteristics:* The lack of technological knowledge and awareness about the e-learning system would reduce the learner's confidence. It is considered an essential factor because it automatically slows down the learners' performance in the online platform.
- *Technology awareness:* Internet self-efficacy and computer self-efficacy are the two variables that determine technology awareness. Lack of computer self-efficacy of the learners is the main reason for the failure of the e-learning system. The lack of computer self-efficacy will reduce the confidence level of users to use the computers.

Case 2: Gender-based e-learning adoption

From the selected country studies, the constructed are identified and used to measure gender-based e-learning adoption differences. The factors included in this study are:

- *User attitude* – The way the learner takes the online course and a positive attitude will improve the users' performance in the learning environment. This study shows that the male users have a more positive attitude towards e-learning than female users because the male users have a more positive attitude and belief towards e-learning adoption.
- *User behaviour* – The collaborative nature and active participation determines the user behaviour in the online platform. The male users are more communicative and involved in the online platform compare to female users.
- *Technology awareness*- The technology awareness of male and female users is low in the Indian context because of a lack of digital literacy. It is considered that technology awareness is not significant to e-learning adoption.
- Perceived satisfaction – This study identified that the male and female users are equally satisfied with the existing e-learning system. Sufficient content availability and adequate Internet facilities would increase user satisfaction.

Case 3: E-learning barriers

With the help of literature supports, the two different e-learning barriers are analysed through this study. They are:

- *Technological barriers:* The discomfort of ICTs use would increase the technological gap in the existing e-learning system. It also indicates that there is no sufficient digital awareness about e-learning and support services. Hence the users are not comfortable with the available tools in the online environment.
- *Individual barriers:* User anxiety is the root cause for the individual barrier and directly reduce e-learning adoption. Thus, the anxiety would reduce the confidence level of users in the online platform.

Case 4: Cloud-based e-learning adoption

The above results confirm that the infrastructure is one of the essential factors in an e-learning system. Therefore, the cloud-based e-learning study is conducted to analyse the factor called infrastructure service.

- *Infrastructure* – The cloud-based infrastructure service, i.e. data centre, is deployed using a cloud simulator. The single and multiple data centres performances are compared using the factors like processing response time, processing time and request servicing times. This study also confirms that the multiple data centre would increase the performance of the cloud-based e-learning system from the management perspective.

On the other hand, quantitative research was utilised to identify the suitable platform (mobile) for promoting e-learning. The quantitative study was conducted in two different ways: first, the various dimension of special education such as special students, technology, teachers, management, Government and economy were identified. As a part of the study, ATDs were reviewed and compared with mobile apps. Finally, the benefits of mobile apps were identified. Second, sentiment analysis was used to determine the awareness level of online users against civic and e-learning. In addition, the e-learning barriers were prioritised using Twitter Sentiment Analysis. The qualitative and quantitative studies' approaches correlated to various dimensions and factors of e-learning, indicating that the studies were structured around similar ideas and structures. This allows the study to be conducted within a broader conceptual framework. As a result, findings from the techniques will be simple to link, validate, and triangulate.

The following aspect is essential to the evidence for triangulation. The findings of quantitative studies revealed that users' perceived usefulness and perceived satisfaction with e-learning encourage users to adopt it. Similarly, the quantitative study's empirical results showed that male users have more technology awareness, a positive attitude, and behaviour toward e-learning than female users. Male and female respondents have the same level of satisfaction with e-learning adoption. Furthermore, the findings of the quantitative studies revealed that in the Indian context, technology and individual barriers influence e-learning adoption. As a result, qualitative research was carried out to confirm the e-learning barriers were preventing e-learning adoption. According to the study, one of the most significant barriers to e-learning adoption is infrastructure. Therefore, quantitative and qualitative research is carried out to identify a suitable platform (infrastructure) to promote e-learning. According to the management perspective, the cloud-based e-learning study is conducted through a quantitative approach. On the other hand, the awareness of the mobile platform is measured through two different quantitative studies i) awareness of mobile apps in special education is measured through an interview questionnaire ii) awareness of mobile apps (such as civics and e-learning apps) among online users through sentiment analysis.

Previous studies identified that lack of infrastructure, improper utilisation and less technology awareness is the main reason for e-learning failure. But only fewer studies reported on e-learning adoption in higher education through users' lens. This study, therefore, contributes to the literature by providing evidence on e-learning adoption in higher education. The findings show that the learners are not satisfied with e-learning system quality. In addition, the learner's computer-self efficacy is low, thus reducing the learner's confidence in the online platform. The study also identified that the discomfort in ICTs use and user anxiety are the other barriers that affect e-learning adoption.

On the other hand, they are only less reported on special school education and about ATDs. The economic factor and technological factors are the most critical factors identified through a qualitative study. The availability, affordability and cost factors of ATDs are more in special schools. Therefore, mobile apps are suggested for special schools to increase availability, affordability and minimise costs. In addition, the awareness of the mobile app in civic and e-learning is compared, and the emotions of online users are extracted. The polarity (positive, negative, neutral) emotions (joy, fear, sadness, disgust, anger, surprise) are analysed through sentiment analysis. It confirmed that the awareness level of mobile apps is more for e-learning than civics learning.

Therefore, it can be observed that quantitative and qualitative studies were closely integrated to validate the study findings. This improved the external validity of the overall research. As discussed in chapter 4, the finding from the quantitative analysis for these variables was inclined to be unstable and was found to be insignificant. i.e., the relationship between the system quality, computer self-efficacy, and learner confidence in e-learning adoption. However, the same result has been identified in the e-learning barrier dimension. The discomfort of ICTs use and user anxiety are the factors that affect e-learning adoption and reduce the success rate.

Meanwhile, the users are satisfied with other qualities like system information, service and collaboration quality. The same result is achieved in gender-based e-learning in that the male and female users are satisfied with the e-learning. This allows the study approaches to be conducted under an overall conceptual framework. The findings obtained from the approaches will be easier to associate, validate, and attain triangulation purposes. Based on the quantitative study, the Technological Learner Barrier (TLB) conceptual framework is proposed and evaluated in chapter 4.

The qualitative components obtained from the interviews are special education dimensions, including special students technology, teacher, management, Government and economic dimensions. In addition, the use of ATDs and mobile apps are compared to assess technology awareness. On the other hand, the discussion of the qualitative analysis obtained from Twitter demonstrates that the level of awareness of mobile apps in civic learning and e-learning and the results are comparable. When the findings were combined with interview data, it was discovered that mobile apps are a better platform for promoting e-learning. When the results were combined with the conclusions of the interviews, a general framework of accepting mobile-assist e-learning and mobile applications was developed. As a result, it would be interesting if future studies could use these models to investigate the impact of the factors and their interactions on the actual use of mobile-assist e-learning applications. The study also identified the crucial components for achieving a suitable e-learning framework in India.

The findings illustrated that system characteristics, learner characteristics, technology awareness, e-learning barriers, special education, government policies, mobile-assisted e-learning and supporting factors influence e-learning adoption. Therefore, it would be desirable to include multi-dimensional variables including learner, technology, management, institution, Government, and economics in the quantitative models. Thus, future research would consider all dimensions in general and special education for studying their combined effect on the mobile platform and the benefits of mobile applications in higher education and special education. Thus, the integration of qualitative and quantitative studies provides a suitable e-learning framework for the Indian education system.

The previous studies identified that infrastructure as one of the main e-learning implementation barriers. Therefore, this study included a cloud platform for analysis infrastructure as a service (i.e., data storage) and measure the data processing time and response time of the datacenters. The result of cloud-based e-learning confirms that the multiple data centres improve the performance of the e-learning, and this study suggests a cloud-based platform to promote e-learning from the management perspective. On the other hand, the study incorporated sentiment and content analysis of the tweets to detect the connection of common themes of mobile apps used in civics and e-learning. The result of mobile-assist learning confirms that mobile e-learning apps awareness is more compared to civics learning apps. The common variables and practices identified through the qualitative analysis.

Table 6.2 Common variables and practices identified through the Qualitative analysis.

Variables/Themes	Twitter Analysis (E-learning barrier)	Interview	Twitter Analysis (Mobile platform)
Mobile apps usage		✓	✓
Mobile apps awareness		✓	✓
Technology	✓	✓	✓
E-learning app	✓	✓	✓
Special education app		✓	✓
Special students		✓	✓
Online users	✓		✓
Parents		✓	
User attitude	✓	✓	
User belief	✓	✓	
Teachers		✓	
Government	✓	✓	✓
Management		✓	
Disability types		✓	✓
ADTs		✓	
Schemes			
Funds		✓	✓
Digital awareness campaign	✓		✓

The study reveals more common variables through qualitative data analysis in Table 6.2, which were considered and studied in three different situations based on their combination.

Case 1: E-learning barrier dimension

The Twitter analytics of the e-learning barrier revealed that various e-learning barriers, including infrastructure and the Internet, are the most commonly observed variables along with system quality and software interface and the digital divide.

- *Infrastructure:* According to the sentiment analysis of Twitter data, infrastructure is one of the most important components from an organisational point of view. The study's findings highlighted the e-learning barrier and confirmed that infrastructure factors are the primary cause of the e-learning barrier. Users' negative polarity (44 per cent) for the infrastructure is verified through sentiment analysis, indicating that users are dissatisfied with the e-learning system. Infrastructure is also the most frequently mentioned theme in both qualitative and quantitative studies.

- *Internet:* Internet infrastructure issues, such as bandwidth and connectivity, have an impact on e-learning adoption barriers. In previous studies, slow Internet speeds and high Internet traffic have been shown to lower the number of individuals who use e-learning. According to the sentiment analysis, the Internet scores 43 per cent negative polarity compared to the infrastructure barrier.
- *System quality and software interface:* A user-friendly e-learning environment is determined by the system quality and software interface. Even though this study shows that online users are dissatisfied with the current e-learning system, only a small percentage of users said the e-learning system's software and interface designs are less user-friendly. As a result, it receives a 6% negative polarity score, among other factors.
- *Digital divide:* The major cause of the digital divide is the country's unequal distribution of digital resources. When compared to rural users, urban users have greater digital resources and Internet access. As a result, it widens the digital divide between regions and limits e-learning adoption. Only 5% of online users stated that they do not have enough digital resources.

Case 2: Special education

The qualitative analysis revealed the various e-learning dimensions and factors in special schools. The most common elements identified in this study are mobile apps usage and mobile apps awareness. In addition, the most common dimensions include in this study are special students, technology, teachers, Government, management and economics.

- *Special student:* In this study, the special student's assistive technology device and mobile apps are designed according to the individual needs. The special students' attitudes and beliefs about technology influence their adoption of mobile apps, which will improve their use in special education.
- *Technology:* Individuals and special students are influenced by assistive technology devices, mobile gadgets, mobile platforms, and apps and are encouraged to use mobile-assist e-learning. In comparison to standard ATDs, special students prefer to use mobile apps. The Rogervoice app, for example, used text chat to assist deaf and hard of hearing students in recovering from their problems.

- *Teachers:* The attitude of special students toward technology is influenced by their teachers' supportive attitude, enthusiasm, awareness, and additional skills. From the instructors' perspective, a special education limitation is the lack of special training programs.
- *Government:* According to the findings, the Government plays a critical role in enacting special education legislation, implementing new schemes and policies, and allocating financing for their advancement. Even though the Government introduced several schemes and ambitious programmes, the schemes are not receiving full benefits due to a lack of coordination.
- *Management:* Many institutions and NGOs have inadequate infrastructure facilities to adopt new technologies in special education. Moreover, there are no proper coordinating systems among the education institutions connected under the same schemes. Due to a lack of funding, it is unable to purchase new ATDs in special schools.
- *Economics:* According to the research, special students' families earn less than the poverty level and do not receive adequate financial assistance. Furthermore, many special education institutions do not receive sufficient funding from government programmes.

6.2.2. Measuring and Reporting Variables

6.2.2.1. Synthesis of Findings for Quantitative analysis

This chapter developed and analysed the Technological Learner Barrier (TLB) model to achieve the research objective. Based on the literature support, the constructs are identified, and data analysis has been performed. The study is carried out through the PLS-Structural Equation Model (PLS-SEM) method. It is used to measure the relationship between latent constructs in the research model. The model proposed in the current study is a complex structural model consisting of constructs adopted from various theories to analyse the relationship between them and enhance research model interpretation. Thus, this study utilised PLS-SEM as suggested by Hair et al., 2018 to test the hypotheses. Table 6.3 illustrated the summary of the hypotheses. The main findings are:

- Data was collected from 704 respondents from various universities in Southern India. The respondents are from various higher education institutions, including central government institutions, state government/institutions, private and public colleges. The questionnaires consist of a five-level Likert item (SD =1 to 5; strongly disagree to agree strongly). The average age of the population was 18-23 (348), 23-30 (300), and above 30 (56), and the majority of the respondents are male (498). Overall, the respondents are familiar with online courses like Coursera (602), edX (450), Udacity (399), Khan Academy (447), Udemy (431), Alison (499), and NPTEL (527).

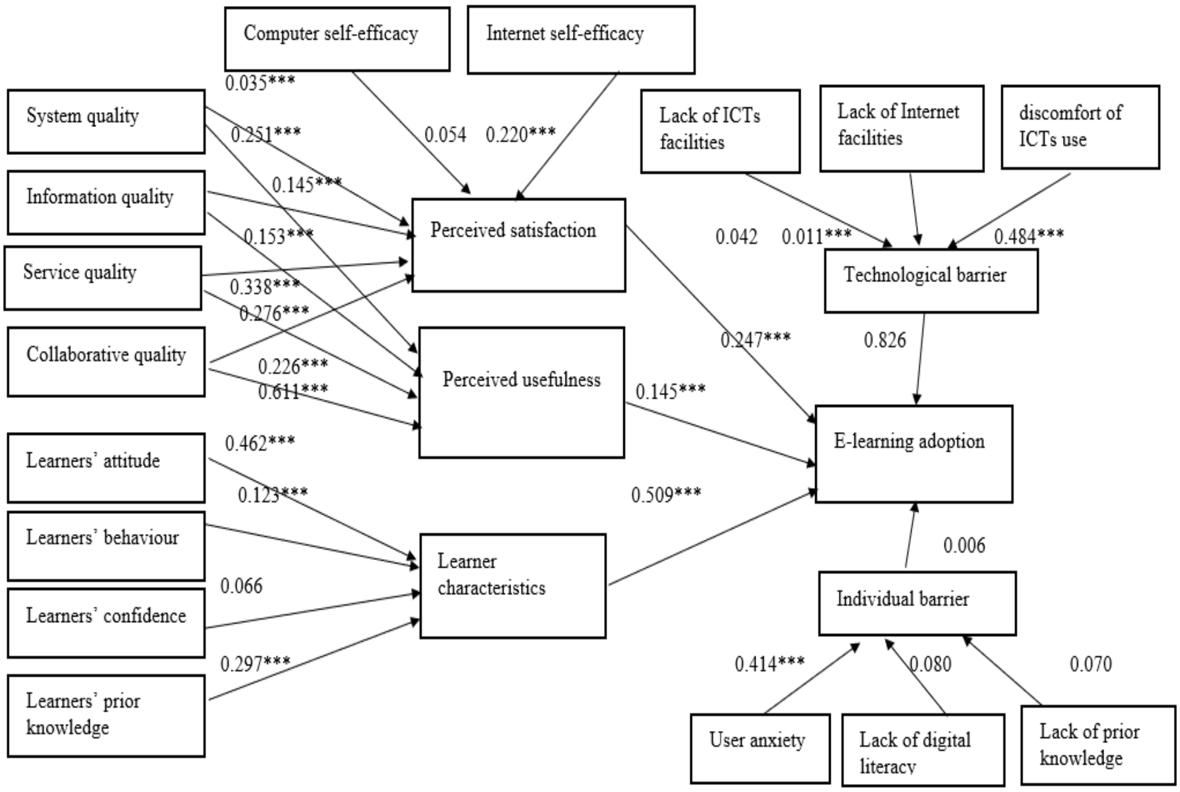


Figure 6.1: TLB Research Model (*Author's own*)

- According to the empirical results, learners are not satisfied with the system quality (p>0.05) of e-learning in the Indian context. Learners are having difficulties to accesses the online portal and navigate in the e-learning environment. Other researchers have concluded the same results in previous research (Cidral et al., 2018;). The lack of computer self-efficacy (p>0.05) and lack of learner confidence(p>0.05) are also not significant in this study. Hence, this study confirms that e-learning implication barriers exist in India. Figure 6.1 illustrates the TLB research model.

Table 6.3: Summary of Hypotheses

Hypothesis	Beta value	Results
H1a: System quality will positively influence perceived usefulness in e-learning adoption.	0.251***	supported
H1b: System quality will positively influence perceived satisfaction in e-learning adoption	0.350	not supported
H2a: Information quality will positively influence perceived usefulness in e-learning adoption	0.153***	supported
H2b: Information quality will positively influence perceived satisfaction in e-learning adoption	0.145***	supported
H3a: Service quality will positively influence perceived usefulness in e-learning adoption	0.276***	supported
H3b: Service quality will positively influence perceived satisfaction in e-learning adoption.	0.338***	supported
H4a: Collaboration quality will positively influence perceived usefulness in e-learning adoption	0.611***	supported
H4b: Collaboration quality will positively influence perceived satisfaction in e-learning adoption	0.226***	supported
H5: Computer self-efficacy will positively influence perceived satisfaction in e-learning adoption	0.054	not supported
H6: Internet self-efficacy will positively influence perceived satisfaction in e-learning adoption	0.220***	supported
H7: Perceived usefulness will positively influence e-learning adoption	0.145***	supported
H8: Perceived satisfaction will positively influence e-learning adoption	0.247***	supported
H9: Learners' characteristics will positively influence e-learning adoption	0.509***	supported
H9a: Learners' attitude will positively influence learners' characteristics in e-learning platforms	0.462***	supported
H9b: Learners' behaviour will positively influence learners' characteristics in e-learning platforms	0.123***	supported
H9c: Learners' confidence will positively influence learners' characteristics in e-learning platforms	0.066	not supported
H9d: Learners' prior knowledge will positively influence learners' characteristics in e-learning platforms	0.297***	supported
H10: Technological barriers are positively associated with barriers affecting e-learning adoption.	0.826	not supported
H10a: Lack of ICTs facilities is positively associated with technological barriers	0.042	not supported
H10b: Lack of Internet facilities is positively associated with technological barriers.	0.011	not supported
H10c: The discomfort of ICTs use is positively associated with technological barriers	0.484***	supported
H11: Individual barriers are positively associated with barriers affecting e-learning adoption	0.006	not supported
H11a: User anxiety is positively associated with individual barriers.	0.414***	supported
H11b: Lack of digital literacy is positively associated with individual barriers.	0.80	not supported
H11c: Lack of prior knowledge is positively associated with individual barriers	0.070	not supported

- The e-learning barrier factors are analysed through empirical analysis, and the result confirms that the technological barrier (0.826) and individual barriers (0.011) affect e-learning adoption. The constructs lack of ICTs (0.42), lack of Internet facilities (0.011), lack of digital literacy (0.80), lack of prior knowledge (0.070) was not significant. Hence, this study confirms that e-learning implication barriers exist in India.

6.2.2.2. Synthesis of Findings for Qualitative analysis

Under qualitative analysis, four different case studies are conducted to evaluate different platforms (mobile and cloud) that provide e-learning services and perform audience analysis. First, the technological challenges in e-learning were prioritised through social media research. The text labelling is done for sentiment analysis through the rapid miner software tool. Second, the usage of mobile apps in special education is analysed and compared with the traditional Assistive Technology Devices (ADTs). Third, the mobile applications used for civic and e-learning services are analysed through sentiment analysis. Finally, the cloud-based e-learning platform is tested using the simulation tool (CloudAnalyst). In the simulation environment, single and multiple data centres are deployed to analyse the computation resource, such as storage (Infrastructure as a Service).

Twitter analysis – E-learning technological barriers

The most popular words related to e-learning barriers or challenges, excluding the hashtags used in Twitter, are infrastructure (5999), Internet (5986), software/hardware (852), and the digital divide (768). Totally, 13,605 tweets were extracted from the Twitter dataset classified by polarity (positive, negative and neutral) and emotions (joy, surprise, anger, sadness, disgust, and fear). The NB algorithm with a sentiment package (R tool) detects various user emotions from the Twitter data set. Our result confirms that the negative polarity is higher for anger (negative=55%), disgust (negative=67%), fear (negative= 87%), and sadness (negative= 85%); and the positive polarity is high for joy (positive=71%) and surprise(positive=63%).

The high negative sentiment for infrastructure and Internet facilities in the results indicate that online users are not satisfied with India's infrastructure and Internet facilities. In this study, the confusion matrix is used to label the text and analyse the model performance. The confusion matrix consists of two classes (Actual and Predicted class) and four parameters (predicated positive and negative, true positive and negative). In our model, the precision rate is 59.90% (pred. positive) and 68.42 (pred negative), and the recall rate are 98.86 (true positive) and 14.36 (true negative), all the values are above 0.5, which denotes the proposed model is good. The overall accuracy measured through the NB model is 60.2%.

Mobile application in special education

The various types of disabilities are classified in special education, and the existing traditional ATDs are compared with mobile applications. This study focuses on various special education factors such as technology, learner, teachers, Government, environment, and economics. Through literature and interviews, it is identified that ATDs for special needs are less available and affordable in India, so this research is being carried out to find a solution. Feedback on ATDs and mobile apps are taken from different stakeholders, and the benefits of mobile apps are compared with traditional ATDs. Our finding confirms the lack of technological support, government support, and economic factors in India, and this study recommended mobile applications to overcome the obstacles.

Comparison of mobile phone-assisted civic and e-learning

The use of mobile phone-assisted services in civic and academic learning is examined in this study. The awareness levels of citizens towards e-service are measured under two separate categories: i) civic learning (which includes cVIGIL, Divyang Sarathi, and Agrimarket) and ii) the education services (which includes SWAYAM, e-Pathshala, and E-CBSE). This case study compares the usage of mobile apps in civic learning and e-learning service using Twitter data. Even though mobile devices are widely used in developing countries like India, awareness of civic learning is less than that of e-learning. The Government initiates many awareness programs through the digital India campaign, which has an excellent reach to the students compared to the public.

Civic learning is a process through which young people develop the knowledge, skills, and commitments to interact effectively with fellow community members to address shared problems. According to Abdulkarim et al. (2018), combining/using e-learning with/for civic learning could improve students’ information literacy. Similarly, a study by Japar et al. (2019) revealed that Civic education through e-learning have increased the critical thinking ability and creativeness of students. Ahmed and Gul (2021) found that online learning is a useful approach for promoting social justice attitudes and civic attitudes of students.

As mobile apps are considered as an essential platform for improving civic and e-learning services (Hahn, 2014), many government schemes promote m-learning apps for civic learning and academic learning among their citizens. The Indian Government has introduced many mobile apps to encourage civic and e-learning services among citizens.

In this thesis, selected civic learning apps (cVIGIL, Divyang Sarathi, AgriMarket) are compared with selected e-learning apps (SWAYAM, ePathshala and E-CBSE) to analyses the awareness of the m-learning platform. This case study examines how these mobile apps improve civic and e-learning services, as well as citizen digital awareness. It also enables an effective digital service to help Indian citizens overcome their lack of digital literacy. The purpose of this study is to use social media analytics to assess citizens' digital awareness.

Cloud-based e-learning

The e-learning service based on a cloud platform is analysed from single/multiple data centre dimensions. Despite developing e-learning infrastructure, the benefit of the cloud platform is often adopted. The cloud-based e-learning simulation environment is created using a Cloud- Analyst tool. The cloud's efficiency is analysed based on e-learning hosted on a single data centre and multiple data centres. The service time and overall response time of the data centre are analysed through CloudAnalyst. This study confirms that the adoption of cloud services will improve e-learning efficiency through cloud infrastructure services. The data centre models' response time is estimated, and it is also shown that multiple data centres improve load balancing at the application level. Also, the two models were compared, and the multiple data centre models are recommended for real-time implementation.

Causal Loop Diagram

Causal diagrams can be thought of as a language. This language's syntax is built up from causal loops, which are like sentences constructed by linking together variables of importance and showing the causal relationships between them. In other words, causal loop diagrams can be thought of as sentences that are constructed by identifying the key variables in a system and indicating the causal relationships between them via links.

The words with arrows coming in and out represent variables, or quantities whose value changes over time and the links represent a causal relationship between the two variables (i.e., they do not represent a material flow). A link marked “+” indicates a positive relation where an increase in the causal variable leads, all else equal, to an increase in the effect variable, or a decrease in the causal variable leads, all else equal, to a decrease in the effect variable. A link marked “–” indicates a negative relation where an increase in the causal variable leads, all else equal, to a decrease in the effect variable, or a decrease in the causal variable leads, all else equal, to an increase in the effect variable.

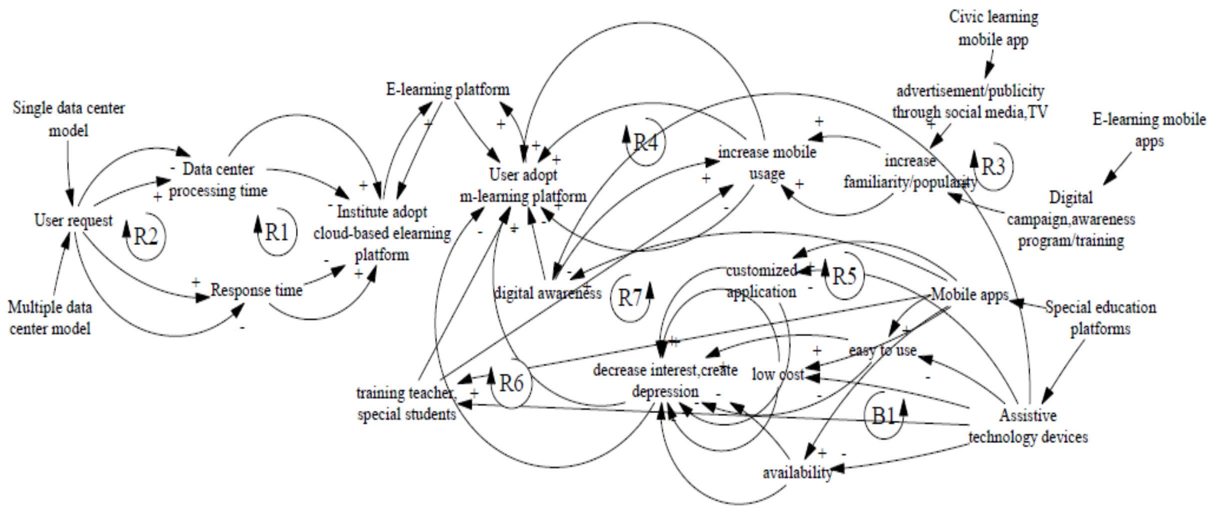


Figure 6.2: Causal Loop Diagram to adopt e-learning platform

A positive causal link can be said to lead to a change in the same direction, and an opposite link can be said to lead to change in the opposite direction, i.e. if the variable in which the link starts increases, the other variable decreases and vice versa. As with the links, feedback loops have either positive (i.e., reinforcing) or negative (i.e., balancing) polarity. Causal loop diagrams concisely capture and communicate cause and effect relationships that can explain dynamic issues in a concise manner. They do not, however, provide a detailed representation of the structure that generates the dynamics. The power of causal loop diagrams is in their ability to capture the reasons systems behave the way they do and portray this understanding in a power graphic manner.

A system thinking technique in the form of a causal loop diagram (Chen, 2011; Mutingi, 2014; Sedarati & Baktash, 2017; Fisher et al., 2000) was used to identify and analyse the influence of these factors involved in various platforms to promote e-learning services, including mobile and cloud. The causal loop diagram, which is widely used for understanding and visualising interrelationships in the form of causal connections (positive and negative) and causal loops (balancing and reinforcement), has been used to study e-learning adoption in India.

Inference from CDL:

According to the first reinforcing loop R1, named as “single data centre model”, the increase in user requests lead to an increase in data response time and thus decrease the performance of cloud-based e-learning platform adopted by the institution. Similarly, in the single data centre model, the increase in user requests leads to an increase in data centre processing time, which in turn decrease the institute adoption of the cloud-based e-learning platform. In the second reinforcing loop R2, in multiple data centre models, user requests increase than data response time decrease compared to single data centre model, which increases institute adopt cloud-based e-learning platform. Likewise, user request increase than data centre processing time decrease compared to single data centre model, which improves the institution's performance of cloud-based e-learning platform

The third reinforcing loop, R3, is named "civics learning" in the civics learning mobile app. If the advertisement/publicity through social media and TV is increased, it improves familiarity/popularity, increasing mobile usage and user adoption m-learning platform. The fourth reinforcing loop, R4, is named "e-learning mobile apps". If a digital campaign or awareness program/training is introduced, it increases familiarity/popularity, which increases mobile usage, and users adopting the m-learning platform.

The fifth reinforcing loop, R5, is named "special education." In special education platforms, mobile apps can customise applications, increase interest, avoid depression, and increase the use of m-learning platforms. Mobile apps are easy to use and low cost, which attracts learners to adopt the mobile platform.

The sixth balancing feedback, B1, represents that the assistive technology devices are difficult to customise, which decreases interest, creates depression, and does not adopt the m-learning platform. Moreover, the cost of assistive technology devices is more and less availability reduces the user interest to adopt the m-learning platform. In special education platforms, the seventh reinforcing loop, R7, in special education platforms denotes that if a user has digital knowledge of mobile apps, they are more likely to use an m-learning platform. Teachers and special students are trained on utilising mobile apps in special education platforms, and then the user prefers to use an m-learning platform for their improvement.

6.3 E-learning Adoption Framework

The synthesis of the study integrates our findings to answer the research question based on the various empirical studies (Wyborn et al.,2018). It will develop new knowledge and improve the applicability based on findings. Understanding the problems from a different perspective and establishing the new operating models will improve the composite knowledge (Carpenter et al.,2009; Hampton & Parker, 2011). Therefore, this study contributes new ideas for the policymakers to develop a suitable e-learning framework for the Indian context.

This study combines qualitative analysis, quantitative analysis, and case studies to develop the proposed framework. The results from various findings are connected, and suggestions are provided for future development. Based on the collective studies, the eight-layered e-learning framework was designed with various dimensions and factors. Finally, this study provides key points to policymakers to improve the e-learning framework for the Indian context.

The literature review synthesis combines various constructs from different studies, which will help determine the research question. The various constructs under different dimensions were identified to make the foundation for the model. The learning theories are used to measure the learners' knowledge level and the learner's outcome. Learning theories are used to identify the learners' characteristics and awareness factors and added to the model to improve the online performance of the learners. On the other hand, the e-learning system factors are identified from various information system theories and included in this study. Meanwhile, gender-based e-learning adoption is analysed as a part of this study. The numerous factors in the e-learning dimension are described (Urbach et al., 2010; Cidral et al., 2018).

In the technology dimension, the various system factors are identified using the D&M IS Success Model. The factors studied under this dimension are system quality, information quality, collaboration quality and service quality (Kim & Park, 2018). The hardware, software, course content, technical support, and e-learning forum design are crucial factors in the e-learning system (DeLone &McLean, 2014). In the e-learning study, the success rate of e-learning adoption was measured based on these factors. Therefore, the above factors are included in the current study. However, the learner dimension measures the learner's self-efficacy in the online environment. The social learning theory and cognitive theory are used to refine the factors under this dimension. Computer self-efficacy, Internet self-efficacy, learner attitude, behaviour, confidence and prior knowledge are measured. In the design dimension, three factors are measured: perceived usefulness, perceived satisfaction and e-learning adoption (Lin & Lee 2006; Lin & Lu 2000; Alexander 2001). Technology Adoption Model and Diffusion of Innovation Theories are reviewed to adopt these factors. The perceived usefulness and perceived satisfaction are act as a mediator in the study.

The implication barriers of the e-learning system are analysed under the e-learning barrier dimension. The two broad classifications identified through literature support are technological barrier (digital gap) and individual barrier (e-learning gap). Digital resources and Internet services are critical factors in the online learning environment. Therefore, the lack and unequal distribution of ICTs, the lack of Internet connectivity and the discomfort of using ICTs are analysed under the digital gap (Bower, 2017). Hence, user anxiety, lack of digital literacy and lack of prior knowledge about the online courses are measured under the e-learners gap (Marco & Kai,2017). This study mainly focuses on the way how the technological and individual barrier affects e-learning adoption.

As a part of the study, the e-learning adoption based on gender difference is also analysed. The various factors analysed are user attitude, user behaviour, technology awareness and perceived satisfaction.

Various theories, such as feminist theory, cognitive constructivism, and social constructivism, are used to identify the factors. (Limerick & O'Leary 2006). The selected countries-based literature review was carried out to determine the factors. The comparisons are made based on individual performance and social behaviour (Vanitha & Alathur, 2020 b). One of the major motivations for conducting this gender-based study in the Indian context is that India's gender inequality index rank is low, which necessitates further research to improve the ranking.

The two different case studies were conducted under the management dimension. Through case studies, e-learning platforms used by the institutions were analysed. The cloud platform is taken from the institution perspective, and the mobile platform is considered on the end-user side. The cloud analyst simulation tool is used to simulate the data centre servers from the institutional perspective. The single data centre and multiple data centres are analysed, and a better platform is prescribed to implement the e-learning system from the institution side. From the end-user perspective, mobile apps are analysed using Twitter Sentiment Analysis. The mobile apps awareness and satisfaction level of users are analysed through Sentiment Analysis. Both civic mobile apps and e-learning apps are considered, and the various emotions of different mobile apps usage are compared and analysed (Saxena, 2018).

Meanwhile, in another case study, the mobile apps assisted for special education is compared with assistive technology devices. The interviews are conducted with the special school students, parents and staff. The technological, learner, teacher, Government, management, and economic factors are measured through qualitative analysis (Tan et al., 2019). The advantage of mobile apps over assistive technology is reviewed, and suggestions are provided to improve special education.

Overall, the audience analysis is carried out through the pedological dimension. This study collects data from three categories: online users, higher education students and special students/parents, staff, and management. The opinion and emotions of different types of users are analysed through empirical analysis. Hence, the results are summarised to design a suitable e-learning adoption framework for the Indian context.

The proposed e-learning adoption framework is suitable for the improvement of the online education system in India. It is very difficult to adopt a global e-learning adoption framework because the implications and challenges faced by countries are varied based on geographical locations and technological development (Nikolopoulou & Gialamas, 2016). This study suggests the e-learning adoption framework appropriate for the Indian context based on empirical results and case studies.

The stakeholders, including the users, teachers, institutions, government agencies, special needs students and their parents, provide the opinions and feedback to improve the e-learning framework. The eight-layer e-learning framework was proposed based on the e-learning dimension. Each layer consists of various factors to improve the online education system in the Indian context. Different dimensions are included in this study are e-learning attributes, learner dimension, technological dimension, barrier dimension, institution dimension, management dimension, design dimension and pedagogical dimension. The proposed framework of e-learning adoption for the Indian context is showed in Figure 6.3.

Layer 1 – E-learning system attributes: Asynchronous and synchronous are the two different modes of services offered by the e-learning system (Weiser et al., 2018). In former service, it supports learners to learn when both teacher and learner are not online simultaneously. It allows the learner to download the content, upload the assignments, and share ideas with peers and teachers anytime (Amasha & AbdElrazek, 2016). It improves the student's ability to process the information because they have enough time to comprehend the message (Hrastinski,2008; Amirkhanpour et al., 2014). On the other hand, the asynchronous mode has some limitations, like the students may feel isolated from the learning environment because it is not collaborative.

Meanwhile, the synchronous mode creates a collaborative environment to share knowledge and ideas among teachers and peers (Gronlund & Islam, 2010). The advantage of synchronous mode is the students are committed, motivated and active in the online environment (Holmes & Gardner, 2006). But the limitation is only less complicated issues, and planned tasks are discussed in the online environment compared to traditional classroom learning.

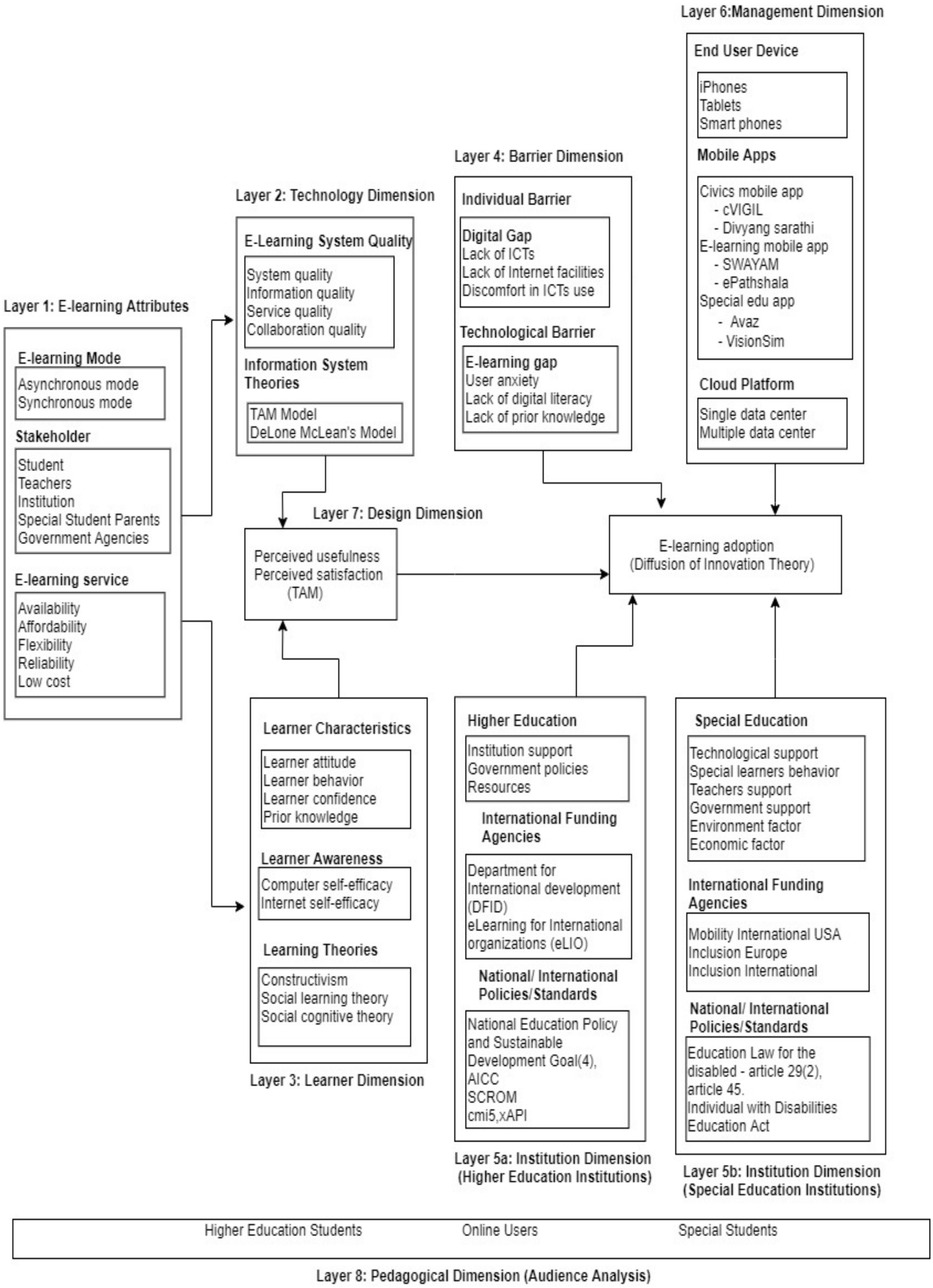


Figure 6.3: Proposed Framework of E-learning adoption for the Indian context

The stakeholder's feedback will directly or indirectly help to improve the framework. In which the learners are the main stakeholder, for whom the whole e-learning set-up is provided. The technology awareness and willingness of the learners are measured, and feedbacks are taken for future improvement (Wang, 2003). The teachers and parents of special students are included in this study to measure the awareness level of special students about mobile app usage. Overall, the institutions have the responsibility to provide quality e-learning services to the learners. Therefore, the institutions merged with government agencies to get financial support. The Government has announced many schemes and projects to enhance the e-learning standard globally. This study analyses infrastructure, Internet, technical support, and financial supports based on government policies and schemes. The special school teachers are directly involved in this study to provide feedback about the special school students. The standard online platforms like Coursera, edX and NPTEL are used to analyse students' willingness to adopt an e-learning environment.

The outcome of the e-learning service is measured using factors likes availability, affordability, reliability, flexibility and cost factors (Ismaili, 2017). The availability factor includes technical support, financial support, and the availability of another online resource required to complete the online course successfully (McPherson & Nunes 2008). The penetration of the Internet in India increases the affordability of e-learning services to higher education. This is because the Internet penetration rate in India is 5.4% among one million users (Rao, 2011). The adequate infrastructure and Internet facilities provide reliable service in the online platform. Thus, the reliability of ICTs is considered as one of the essential factors to adopt e-learning services (Urbach et al., 2010).

The e-learning service provides a user-friendly environment to access the course according to the learner convenience. This is because the entire e-learning environment is designed learning-centric, encouraging learners to become more self-direct (MacGregor & Turner, 2009). Thus, the flexibility service attracts many learners to the e-learning system. Finally, the cost is considered as one of the most critical factors in the e-learning design. This is because the online course aims to provide quality education at a minimal cost (Cherukulath & Sivakumar, 2017). Many authors suggest that financial factors would affect the adoption of e-learning systems from the learner's perspective (Ilin, 2020). Therefore, the minimal cost or financial support provided to the online courses would encourage the learner to adopt the e-learning system more quickly (Romiszowskr 2004; Ruth 2010; Wang & Shee, 2007). The data collected from various users and social media data are given as input to the framework. The opinion of different users is integrated to develop a suite e-learning framework. The inadequate technical resource and lack of awareness are identified as important factors among Indian users. Meanwhile, this framework measures -learning outcomes through availability, affordability, flexibility, reliability and cost factors.

Layer 2 – *Technology dimension:* The system quality parameters are identified using Information System theories. TAM model and DeLone & McLean's model are combined to frame this layer (DeLone &McLean, 2014). The e-learning system quality is evaluated based on ICTs & Internet facilities provided in the online environment (Cidral et al., 2018). The content quality, e-learning platform including hardware and software service and technical support are also analysed.

Layer 3 – *Learner dimension:* The learner dimension constructs are designed based on the learning theories (Ray et al., 2019). The various learning theories like constructivism, social learning theory, and social cognitive theories are reviewed to develop this layer (Liaw & Huang, 2010). The learner's characteristics, computer awareness, and Internet usage are also analysed (Parkes et al., 2015; McGill et al., 2014). Overall, the learner's characteristics and technology awareness about online courses are evaluated. Information system and learning theories are considered as a foundation for developing the e-learning system characteristics and learner characteristics. This technological dimension is validated through various theories like D&M IS success model and the TAM model. Whereas the learner dimension is measured using learning theories like social learning theory and constructivism

Layer4 – *Barrier dimension:* The e-learning system faces various challenges during implementation in higher education institutions. This study identifies and analyses individual and technological barriers (Chipevaa et al., 2018; Choudrie Choudrie). The unequal distribution of resources creates a digital divide issue in the e-learning system (Van Deursen et al., 2017; Kim & Park, 2017). To fill the above problems, recommendations are provided in the conclusion section. The e-learning system developer should consider the e-learning barriers, including technological and individual barriers, to promote reliable e-learning services. To achieve the third target of SDG4, these barriers should be reduced to provide quality education.

Layer 5 – *Institution dimension:* In this study, two different educational institutions are considered: higher education institutions and special schools. Usually, education institutions get financial support from funding agencies from both national and international bodies. The Department for International Development (DFID) and eLIO are some international funding agencies that support online courses in India. Meanwhile, the Indian Government also introduced education policies and schemes to improve e-learning services. The e-learning service quality is verified by various e-learning standards like ALCC, SCROM, CMi5, XAPI (Frydenberg 2002; Mohan 2004; Tawsopar & Mekhabunchakij, 2013). The main aim of the National/International policies and the standard is to achieve and fulfil educational goals. Through the literature support, it is identified that the infrastructure and financial crisis are the main problems to implement e-learning services in the institution. Second, special education is reviewed under the institution dimension. The various traditional ATDs used in special schools are compared to mobile apps. The importance of mobile apps over ADTs are analysed, and the benefits are listed out. The various international agencies funded to develop mobile apps are Mobility International USA, Inclusion Europe, Inclusion International is included in the framework. The International/National policies/standards that evaluate the special education standard are identified and included in the framework: Education Law for the disabled-article 29(2), article 45, and Individual with Disability Education Act. Both higher education and special schools follow their standards to satisfy quality education. Various policies, schemes, institution support factors and international funding agencies are also included in the institute dimension to promote flexible e-learning services. The special school management should consider the special student's finical status and encourage them to use the mobile application in the teaching-learning process. The organisation also approaches the international funding agencies to provide a better special education environment.

Layer 6–*Management dimension:* The various e-learning platforms are reviewed under the management dimension. Mobile apps are considered on the end-user side, whereas the cloud platform is analysed under the institution dimension. The mobile usage and awareness about the mobile apps were analysed using the empirical study. Besides, the awareness of e-learning apps and general civic apps were compared through sentiment analysis. As a result of this study, the different types of special education mobile apps are also recommended to improve special education. The management must consider the cloud platform and mobile to promote reliable e-learning from the management and user perspectives. It is identified that the lack of infrastructure, including server, database, bandwidth, software and other network utilities, are inadequate in India. Therefore, the management should consider a cloud platform to promote e-learning services from an institutional perspective. Meanwhile, due to the high usage of smartphones and more Internet penetration, the management should consider mobile platforms to promote e-learning services from the user perspective.

Layer 7 *– Design dimension:* Learner’s technology awareness, usage and satisfaction are measured in this dimension. The TAM model identifies the constructs, namely perceived usefulness and perceived satisfaction, that measure e-learning adoption.

Layer 8 *– Pedagogical dimension:* The audience analysis is carried out as a part of the study. This study deals with three different types of users: higher education students, online learners, and special school students. The responses were collected from the higher education student using the quantitative questionnaire survey method and from the special school students using the qualitative method. In addition, sentiment analysis is also performed to measure the emotions of the online user towards mobile apps. Meanwhile, the user awareness about the e-learning apps and civic apps are compared through sentiment analysis. The opinion of different users was analysed, and a reliable e-learning system is provided through this study.

C H A P T E R 7

C O N C U L S I O N S

Chapter 7
Conclusions

7.1 Introduction

The main aim of this study was to improve e-learning adoption in the Indian context. Based on the e-learning dimensions, the analysis was performed. The conclusion chapter provides an overall summary of the research by revisiting the research question and objectives. Then the key learning from the synthesis of the studies is explained. The study contribution, limitations, and future work are discussed. Finally, the conclusion of the research is drawn with the help of research findings.

The structure of this chapter is as follows. Section 7.2 summarises the empirical study findings with the research objectives. The research questions are summarised in Section 7.3, and the answer is discussed in Section 7.4. This study contribution is highlighted in Section 7.5. Section 7.6 discusses the study novelty, whereas section 7.7 discusses the thesis limitations. Section 7.8 contains research plans for the future. Finally, section 7.9 brings this chapter to a conclusion.

7.2 Summary of the Empirical Study Findings

Under the research objectives described in Chapter 3, the research findings might be summarised. This section summarises the key findings of empirical studies from the quantitative and qualitative research discussed in Chapters 4 and 5. The findings presented in this section combine data from quantitative and qualitative analyses and conclusions derived from a mix of different study methodologies.

This section examines the findings related to all five research objectives to make the discussion simpler and easier to understand. The quantitative study findings regarding e-learning adoption factors and gender-based e-learning adoption are presented in section 7.2.1 (RO1). The quantitative study results examining the e-learning implementation barriers in the Indian context are presented in section 7.2.2 (RO2). Finally, in section 7.2.3, the appropriate platforms for promoting e-learning are examined through several case studies (RO3). Finally, section 7.5 provides recommendations for improving e-learning adoption (RO4) and explains the e-learning adoption framework (RO5).

7.2.1. Factors influencing e-learning adoption

Research Objective 1*:* To study the factors that influence e-learning adoption.

The approach followed to achieve the main research objective of studies on e-learning adoption and gender-based e-learning adoption has been divided into two sections. In the first section, various information system theories (Technology Acceptance Model, DeLone and McLean Models, Diffusion of Innovation Theory) and learning theories (cognitivism, behaviourism, constructivism) are used to identify e-learning adoption factors. Based on selected country studies and learning theories, the significance of the factors influencing gender-based e-learning was confirmed in the second section (feminist theory).

i) Factors influencing e-learning adoption

This research explores the elements that influence e-learning adoption based on a literature review on e-learning, its system characteristics, learner characteristics, other information systems and learning theories. In two e-learning dimensions, it identifies the silent factors that influence e-learning adoption. By evaluating information systems and learning theories, the study model is aimed to combine the aspects that influence e-learning adoption. It focuses on improving e-learning quality and user awareness, both of which contribute to increased e-learning adoption. System parameters are identified and used in this study based on the information success system theory. Computer and Internet self-efficacies are used to evaluate a learner's technology awareness. The perceived usefulness and level of perceived satisfaction are calculated based on these parameters. Learner attributes are also examined, including learner attitude, learner behaviour, learner confidence, and previous knowledge of e-learning.

The following are the key findings from the data analysis of higher education students:

- The study is based on 704 valid responses. The population's average age was 18-23 (348), 23-30 (300), and above 30 (56), with the majority of the participants were male (498). The study population was divided into three categories: central Government (447), state government (144), and private institution (113), with bachelor's degrees (439), master's degrees (207), and advanced graduate/PhD degrees (58). In all, 704 students have taken online courses from Coursera (602), Edx (450), Udacity (399), Khan Academy (447), Udemy (431), Alison (499), and NPTEL (527) are considered for testing the hypothesis.

- The technology dimension is validated through information system theories. The learners believe that attending online courses improves their learning performances. Hence, the finding shows that the relationships between the variables SQ and PU(H1a), IQ and PU(H2a), SE and PU(H3a), and CQ and PU(H4a) are found to be significant at $p<0.001$.
- The learners' Internet self-efficacy is higher due to the increased Internet penetration rate and smartphone usage. The perceived usefulness of the e-learning system is enhanced by prior Internet expertise and use. Even though the learners' Internet self-efficacy (H6) is significant at $p<0.001$, the computer self-efficacy is not significant ($p=0.109$). Hence the relationship between CS and PS (H5) is insignificant. The findings reveal that students have a lower level of digital awareness. In the Indian context, a key issue is identified as a lack of technological awareness.
- The learners who are satisfied with the information quality (H2b), service quality (H3b) and collaboration quality (H4b) of the e-learning system are found to be significant at $p<0.001$. Even though system quality is one of the critical factors in the e-learning system, higher education students are not satisfied with the system quality ($p=0.374$). Hence, the relationship between SQ and PS (H1b) is insignificant.
- The learner dimension is validated through learning theories. The learner attitude (H7), learner behaviour (H8), and prior knowledge (H10) positively impact learner characteristics, and it was found to be significant at $p<0.001$. This self-paced learning attitude improves user characteristics and determines e-learning adoption. Even though other factors have significance with learner characteristics, learner confidence ($p>0.05$) is not significant in this study. This shows the students' lack of confidence in using online resources and lack of communication with peers and educators.
- Prior knowledge is added as one of the constructs in the research model. Among learning theories, the learners' prior knowledge comes under constructivism theory. This theory's unique feature is that according to this theory the learner can process the information based on previous experience and environmental factors

(Duffy & Jonassen, 1991). It links new information with prior knowledge and interprets it accordingly. This thesis contributes to the literature related to prior knowledge in e-learning adoption and the current study confirms that it would positively influence learner characteristics in the e-learning environment.

ii) Gender-based e-learning adoption

Only a few studies looked at the elements that influence e-learning adoption, as well as gender differences. On the other hand, previous research has not examined the gender gap in online courses such as Coursera, Edx, NPTEL, etc. The major goal of this study is to use a constructivist method to identify gender differences in e-learning adoption. It has been examined using four structures: user attitude, technology awareness, perceived satisfaction, and user behaviour. Based on the constructivist learning theory, these components are identified.

- The study is based on 425 valid responses. 425 students have taken more than two online courses in the last year, with males (219) and females (206).
- The population's average age was 18-22 (M=163; F=121), 23-26 (M=37; F=61), and above 26-30 (M=19; F=24), with the majority of the participants were male (219). The study population was divided into three categories: central government (M=109; F=87), state government (M=65; F=79), and private institution (M=45; F=40), with bachelor's degrees (M=149; F=135), master's degrees (M=48; F=50), and advanced graduate/PhD degrees (M=22; F=21). In all, 704 students have taken online courses from Coursera (M=197; F=154), edX (M=112; F=98), Udacity (M=92; F=106), Khan Academy (M=56; F=61), Udemy(M=102; F=86) Alison (M=121; F=73), and NPTEL (M=186; F=113) are considered for testing the hypothesis.
- The UA and EA (H1a) is significant at $p<0.001$, and H1b is insignificant; hence, the study confirms that the user attitude towards e-learning adoption is more for male users than female users. This is due to male users' positive attitudes on e-learning, their ease of use and confidence.
- TA and EA (H2a, H2b) are insignificant, and hence, the users' technological awareness is low for both genders in the Indian context. It implies that both male and female users of the e-learning platform have a lack of technology awareness.
- PS and EA (H3a, H3b) are found to be significant. Hence, the findings show that both men and women are satisfied with the e-learning platform. As a result, there

is no significant difference in perceived satisfaction during e-learning adoption based on gender.

- UB and EA (H4a) are found to be significant at $p<0.001$, and H4b is insignificant. According to the current study, male users' behaviour in the e-learning platform is much higher than female users' behaviour because male users participate in collaborative learning more actively than female users.

7.2.2 E-learning barriers

Research Objective 2*:* To identify the e-learning implementation barriers in the Indian context.

An empirical test was conducted in this study, and critical e-learning barrier components were identified. The findings found that the digital divide was driven by an improper allocation of digital resources, which slowed e-learning adoption. Furthermore, a lack of digital literacy and awareness among users created an individual barrier. Although the current study findings support previous e-learning studies, it also extends further than it on many levels.

The approach followed to achieve the main research objective of the e-learning barrier has been divided into two sections, supported through hypotheses. In the first section, various e-learning barrier factors are identified through empirical study. In the second section, the e-learning barriers are prioritised using Twitter Sentiment Analysis. The following are the key findings from the data analysis of higher education students:

i) Results from an empirical study on E-learning barriers

- A total of 704 valid replies were included in the research. The average age of the participants was 18-23 (348), 23-30 (300), and above 30 (56), with males accounting for the majority of the participants (498). The study population was divided into three categories: central Government (447), state government (144), and private institution (113), with bachelor's degrees (439), master's degrees (207), and advanced graduate/PhD degrees (58). 704 students (602 from Coursera, 450 from Edx, 399 from Udacity, 447 from Khan Academy, 431 from Udemy, 499 from Alison and 527 from NPTEL) have attended online courses and are being considered for testing the hypothesis.

- According to the result of the study, the relationships between the variables LICTs and TB (H1) and IF and TB (H2) are insignificant, which confirm that the ICTs facilities and Internet facilities are adequate. At the same time, the DICTs and TB (H3) are significant at $p<0.01$, which shows that the learners are not comfortable using the ICTs.
- The study findings show that the correlations between TB and EA (H4) and IB and EA (H8) are significant at $p<0.001$ and $p<0.05$, respectively, indicating that the technological barriers and individual barriers affect e-learning adoption.
- The constructs LDL and IB, LPK and IB, are insignificant, indicating that the lack of digital literacy and prior knowledge does not influence individual barriers. On the other hand, the UA and IB are significant at $p<0.001$ and confirm that user anxiety is the main reason for the individual barrier.

ii) Twitter analysis

Various technological challenges are identified in this study, and the most relevant component is determined. The recommendations made in this study will help in reducing technological problems in the e-learning system implementation.

The following are the key findings from the data analysis of online users:

- Through sentiment analysis, the polarity and emotions of Twitter users about the e-learning barrier (infrastructure, Internet, software/hardware, and digital divide) were examined.
- The most popular words related to e-learning barriers or challenges, excluding the hashtags used in Twitter, are infrastructure (5999), Internet (5986), software/hardware (852), and the digital divide (768). Totally, 13,605 tweets were extracted from the Twitter dataset classified by polarity (positive, negative and neutral) and emotions (joy, surprise, anger, sadness, disgust, and fear).
- The accuracy of the model (60.2%) is measured using the confusion matrix through the Naive Bayes method.

TLB Model

Based on quantitative studies, the Technological-Learner-Barrier (TLB) conceptual framework is proposed and evaluated. 704 people from various universities in Southern India were surveyed. The responders were from various higher education institutions, including national, state, private, and public institutions.

The following are the key findings from the data analysis of higher education students:

- Overall, the respondents are familiar with online courses like Coursera (602), edX (450), Udacity (399), Khan Academy (447), Udemy (431), Alison (499), and NPTEL (527).
- According to the empirical findings, learners in India are not satisfied with the system quality of e-learning (p=0.350). Learners are experiencing difficulty navigating in the e-learning environment and using the online portal.
- In this study, the lack of computer self-efficacy (p=0.106) and learner confidence (p=0.67) are insignificant. As a result, this study reveals that India has e-learning implementation barriers.
- Empirical analysis of the e-learning barrier factors reveals that the technological barrier (0.847) and individual barriers (0.772) have an effect on e-learning adoption. Lack of ICTs (0.42), Internet facilities (0.769), digital literacy (0.184), and prior knowledge (0.369) were not significant constructs. As a result, this study reveals that India has e-learning implementation barriers.

7.2.3. E-learning platform

***Research Objective 3*:** To analyse the e-learning platform with case studies of existing initiatives

This chapter explains the purpose of the qualitative analysis conducted in this study. Three different case studies are conducted to examine various platforms' ability to promote e-learning services. First, an interview-based case study was performed on a special school to evaluate the benefits of mobile apps over traditional ATDs. Second, the level of awareness of mobile apps for civic learning and e-learning is analysed using Twitter Sentiment Analysis, and the results are compared. These qualitative studies aim to explore the e-learning platform through case studies of relevant initiatives (research objective 3). Third, cloud-based e-learning was deployed, and the performance of the model was analysed.

i) *Special education*

According to the literature, ATDs for special needs are less available and affordable in India, and hence this study is being conducted to find a solution. As a result, this research focuses on various special education factors such as technology, learners, teachers, the Government, the environment, and economics.

Through literature and interviews, it is identified that ATDs for special needs are less available and affordable in India, so this research is being carried out to find a solution. Therefore, this study focuses on various special education factors such as technology, learner, teachers, Government, environment, and economic factors. Various stakeholders provide feedback on ATDs as well as mobile apps, and the benefits of mobile apps are compared to traditional ATDs.

The following are the key findings from the data analysis of special education students:

- This survey included institutions from various locations (only urban areas). There were 23 special students (14 men and 9 women) ranging in age from 12 to 32
- In addition, the teachers (6 men and 10 women) whose ages ranged from 25 to 56 years were involved in this study. All these teachers taught in special education groups, except two special trainers in the special teacher training institutes. These two trainers partly taught in the special education group and partially trained the teacher training students in the regular classes.
- Furthermore, the teachers in this study (6 men and 10 women) ranged from 25 to 56 years old. All teachers taught special education students, except two special trainers who taught in special teacher training institutes and regular classes.
- Totally 43 in-depth interviews were conducted with the stakeholders (special students parents, teachers, and management staff).
- The content analysis was performed to analyse the presence of themes in the qualitative research. The result of the study reveals that the major factors that influence the special education system are economic factors (30.23%), followed by technology (23.26%), government (18.60%), management (11.63%), teachers (11.63%) and special students (6.98%).
- The study confirms that “economic factors” is the most important factor that slows down the special schools' performance in the Indian context. Therefore, mobile apps are recommended to improve the livelihood of special students.

ii) Mobile assisted e-learning

This study investigates the usage of mobile-assisted services in civic and e-learning. Citizens' awareness of e-services is measured in two categories: civic learning, such as cVIGIL, Divyang Sarathi, and Agrimarket, and educational learning, such as SWAYAM e-Pathshala and E-CBSE.

The following are the key findings from the data analysis of online users:

- Totally, 30421 tweets were extracted from the Twitter dataset classified by polarity (positive, negative and neutral) and emotions (joy, surprise, anger, sadness, disgust, and fear).
- As a result, the Divyang Sarathi scored 91.27 per cent positive tweets in civic learning mobile apps, 7.84 per cent for cVIGIL, and 3.78 per cent for Agrimarket.
- E-learning apps are more well-known among users, with 24.20 per cent in ePathshala, 15.43 per cent in E-CBSE, and 8.23 per cent in SWAYAM.
- The precision rate in our model is 81.72 per cent (predicted positive) and 59.09 per cent (predicted negative). At the same time, the recall value is 99.64 per cent (true positive) and 7.14 per cent (true negative) (true negative). As a result, the model's accuracy using the Naviye Bayes technique is predicted to be 81.42 per cent.
- In comparison to other apps, the e-Pathshala mobile app has a higher overall score. This is because the experts from Indian institutions produce extensive curriculum-based interactive e-content for e-Pathshala.
- This study revealed that the users' awareness of e-learning mobile apps is higher than civic learning apps in the Indian context.

iii) Cloud-based e-learning

Many countries, including India, are facing inadequate infrastructure and Internet bandwidth issues as an e-learning barrier. A high-quality online course necessitates adequate Internet access and high-end video/graphics hardware. Therefore, this research examined a cloud-based e-learning platform to address the problem of insufficient infrastructure.

The following are the key findings from the management perspective:

- According to the Asian zonal time, the online platform is simulated. Between the hours of 13.00 and 22.00, it is expected that online users are active for 7 hours per day.

- By default, 1/10 of users are estimated to be active during peak and off-peak hours. Between the hours of 13.00 and 22.00, it is expected that online users are active for 7 hours per day.
- In the cloud-based e-learning simulation environment, only 15,00,000 online learners are reflected. In this study, 50% of the student population is taken into consideration.
- The application deployment consists of 50 virtual machines (VMs) with a total bandwidth and memory of 1000 MB. Xen-VMM with LINUX-OS, 86 architecture is used in the data centre. With one physical hardware unit, the cost of hosting the online course in an e-learning environment is: "cost per VM$/hr is 0.1, memory cost$ is 0.05, storage cost$ is 0.1, and data transmission cost$/Gb is 0.1."
- The datacenters' physical infrastructure includes 2 GB of RAM and 10 100 GB dual-channel SAS discs for storage. With VM time-sharing policy, there are 4 processors with a processing speed of 10000.
- The data centre requesting time, service time and overall response time of a single data centre is significantly high compared to multiple data centres. Thus, it is confirmed that the deployment of more datacenter in different places will increase the efficiency of an online course in the cloud platform.
- Compared to a single data centre, the overall response time of the multiple data centre is less. This is because of the additional infrastructure supplied for the online course. The key cause for the improvement is the policy of using the closest data centre service broker.

Summary of the Study Findings:

Table 7.1 summarises various studies conducted as a part of this research and their findings.

Table 7.1 Overview of studies conducted as a part of the research

Data set	Sample size/ sampling technique	Methodology	Findings
Primary data set (Questionnaire Survey)	704/convenience sampling	Quantitative method	Influencing factors for e-learning adoption were identified.
Primary data set (Questionnaire Survey)	704/convenience sampling	Quantitative method	The technological challenges in the Indian context were identified.
Primary data set (Questionnaire Survey)	425/ purposive sampling	Quantitative method	The e-learning adoption based on gender difference was analysed.
Primary data set (Semi-structured interview)	43 interviewers/ purposive sampling	Qualitative method	The assistive technology devices used in special education were compared with the mobile applications. It was found that the mobile-based app is more suitable for special students.
Secondary data set (Twitter)	13605 tweets	Case study	The e-learning challenges are determined based on sentiment analysis.
Secondary data set (Twitter)	30421 tweets	Case study	The user awareness of civics and e-learning mobile apps were analysed and compared using sentiment analysis.
Simulation	Cloud analyst	Case study	The e-learning infrastructure service is simulated using the Cloud Analyst tool. Two different data storage (single and multiple data centres) were deployed and evaluated. A better cloud-based e-learning infrastructure is suggested for the improvement of e-learning in the Indian context.

7.2.4 Recommendations

***Research Objective 4**: To bring out recommendations for improving e-learning adoption.*

Based on RO1, RO2 and RO3, the research gaps of the study were identified, and recommendations are provided for improving the e-learning adoption. The suggestions are given under the policy dimension. It would be helpful for policymakers to develop a suitable e-learning framework for Indian universities.

The following are the key findings of the study:

- This study analyses the system and learner attributes that influence e-learning adoption. It identifies the silent factors towards e-learning adoption in two e-learning dimensions. The research model is designed to integrate the factors that influence e-learning adoption by reviewing information systems and learning theories.
- This study analyses e-learning barrier dimensions and factors to improve e-learning system implementation in the Indian context. As a result of this study, the model identified relations between various constructs that affect e-learning adoption.
- To establish a constructive systemic model in the teaching-learning environment, the study employs various information systems theories, including TAM, DeLone and McLean Models and Diffusion of Innovation Theory.
- Learning theories provide the appropriate instructional framework for how information is handled, knowledge is formed and transferred to the learner in the learning environment. The various learning theories used in this study are cognitivism, behaviourism, constructivism and feminist theory.
- The study identified the e-learning barrier factors which affects e-learning adoption in the Indian context. The technological and individual barriers that affect e-learning adoption were analysed through empirical research.
- The study reveals that the economic need of the special students is inadequate, and the financial support is required for them to improve their livelihood.
- In the current study, the digital platform was identified as an effective tool to promote e-learning services. Hence, the author suggests mobile applications as a platform to enhance e-learning services among Indian users.
- On the other hand, this study recommends cloud-based e-learning services to overcome inadequate infrastructure issues.

7.2.5 E-learning framework

***Research Objective 5*:** To develop an e-learning framework to improve e-learning adoption in the Indian context.

The purpose of the study is to provide a successful e-learning adoption framework in the Indian context. The proposed eight-layer architecture consists of various dimensions and factors based on the findings from multiple studies. This study utilised various research techniques, including qualitative, quantitative, and case studies, to develop the e-learning adoption framework.

The key findings of the study are as follows:

- This framework provides a flexible and reliable e-learning system for Indian users. The e-learning system attributes, e-learning system qualities, e-learning barriers, funding agencies, national and international standards and e-learning platforms are included as technical factors. The learner characteristics, perceived use and satisfaction are measured to improve the e-learning adoption among users. The learning theories and information theories are included in this study to measure the learning outcome directly interlinked with e-learning adoption.
- The synthesised results highlight the e-learning influencing factors, barriers, and platform that improves the adoption success rate of e-learning adoption. The mobile and cloud platforms are analysed from the learner and institutional dimensions, respectively. The perceived use and satisfaction are measured to improvise the e-learning adoption framework in Indian.
- The mobile platform promoting e-learning services for higher education and special schools is analysed and confirmed that mobile apps increase the e-learning adoption rate among Indian users.
- In addition, cloud-based e-learning is recommended from an institutional perspective.

7.3. Revisiting the Research Question

This section goes over the research questions from chapter 2 again and tries to answer them with justifications.

Research Question:

How to improve e-learning adoption in the Indian context?

- In India, improper or unequal distribution of digital resources and individual barriers has resulted in the failure of India's millennium development goals.
- It impacts a country's economic development, and numerous innovative digital schemes linked to its long-term development goals have been implemented.
- E-learning adoption framework with mobile and cloud platforms is one such solution that is widely used in low- and medium-income countries, including India, for achieving a better e-learning system

- The content analysis of special education dimensions revealed the major themes such as learner, technology, government, institution, teacher and economic factors. This had helped us in formulating the research question.
- Prior literature in the e-learning domain has also indicated the importance of e-learning systems. Still, it lacks adequate e-learning dimensions, information system theories, and learning theories in the Indian context. Hence this research question was formulated and addressed the importance of e-learning adoption dimensions and factors.
- This approach states that dimensions such as learner, technology, barriers, design, institution, management and pedagogical and e-learning attributes must be considered to achieve a successful e-learning adoption framework.

Therefore, the study considered these components as research objectives and are revisited in the light of multiple case studies and questionnaire surveys across higher education students, special students and online users.

7.4. The Answer to Research Question

During the preliminary study's research, it was discovered that India is suffering from a lack of infrastructure and digital divide issues. In the long run, this could have a significant impact on e-learning adoption. The study reveals that the technological and individual barriers are the challenges that affect e-learning adoption. It has been discovered that various e-learning platforms can help achieve sustainable development goals through improving e-learning platforms such as mobile apps and cloud platforms to reduce the burden of insufficient digital resources. It also became apparent that mobile apps in e-learning can help students get reliable and flexible e-learning services. The awareness and usage of mobile apps to promote e-learning would improve the e-learning adoption of the stakeholders such as higher education students, special needs students and online users. From the management perspective, the cloud-based e-learning platform would improve the efficiency of the e-learning system. In addition, it was determined that using a mixed-method approach was suitable for this study because it allowed for the development of a framework using primary data and secondary data. The following are the key conclusions drawn from this research:

- Implementing a high-quality e-learning system in a developing country like India is still a challenge. Because customising an e-learning system to the demands of an individual or a specific group is extremely challenging. As a result, common parameters from past studies are identified, and more factors are added for improvement.

- To improve e-learning adoption in India, this study examines technology and learner dimensions. Using information system theories and learning theories, the model identified relationships between various constructs in the e-learning system as a result of this research.
- The result indicates that the system quality of the e-learning system is not satisfactory to the learners in the Indian context. The learners felt difficulties navigating the online platforms and reported that the suitable tools are not provided in the online platforms. The learners indicated that they are facing technical issues and a lack of motivation in the online platforms.
- It can be inferred from the findings that the lack of computer self-efficacy is one of the main reasons that reduce e-learning adoption. By using the items like arousal, credibility, knowledge, computer, self-efficacy is measured. The lack of self-efficacy reduces the active participation of the learners in the online environment.
- The study result revealed that the lack of learners confidence reduces e-learning adoption. Due to a lack of motivation, they do not actively participate in online group discussions or share their opinions among peers and instructors.
- The study reveals that the technology awareness of male and female users was low in the Indian context. It can be inferred from the findings that lack of prior knowledge about online courses and lack of computer and Internet self-efficacy are the main reasons to reduce e-learning adoption.
- Interestingly, the study also revealed that male users have a more positive attitude and behaviour in the e-learning environment than female users. This is because male users on the online platform have more positive beliefs, confidence, active participation, and communication with peers and instructors.
- The development of ICTs and Internet facilities has improved economic and social progress in the teaching-learning process during the last few years. However, developing countries like India suffer e-learning difficulties due to a lack of digital resources and unequal distribution of ICTs.

- The e-learning reports, previous literature, and findings confirmed that India suffers from inadequate infrastructure and digital divide issues.
- It has been identified in the questionnaire survey that 704 respondents confirm that the technological and individual barriers affect e-learning adoption in the Indian context. To validate this result, sentiment analysis was carried out for the messages "#elearninginfrastrucutre" posted on the Twitter database.
- Based on Twitter data, the sentiment analysis is performed to measure the emotions of online users. The word analysis and theme analysis were carried on the Twitter dataset. From this, the technological challenges are determined, and the most influential factors are identified. The word analysis was performed based on a sentiment polarity classifier. The sentiment analysis confirmed that the users are not satisfied with the existing e-learning system in the Indian context.
- The result indicated that the learners are not satisfied with the infrastructure facilities and discussed themes related to infrastructure, digital divide, e-learning barriers that consist of negative polarities.
- As identified in the qualitative study, students from special education institutions also suffer from inadequate infrastructure due to the financial crisis.
- The economic factors were found to be the most important factor influencing e-learning adoption among special needs students. The study revealed that disabled students were suffering from economic difficulties as the family income of these students were below the poverty line.
- The family income of the special students is low, and they are not receiving any financial support from the institutions. Hence the economic factor is considered as the most influential factor in special education.
- Interview respondents have also pointed out that they are facing difficulties in using assistive technology devices. They thus indicate that mobile apps are more comfortable and convenient for them to perform their daily tasks and academic activities. Therefore, this study also considers mobile apps suitable for promoting e-learning services among special needs students. For this, data were evaluated from direct observations and 43 in-depth interviews involving special students, instructors and management staff in the special education

institutions.

- To validate this result, sentiment analysis was carried out for the messages "#Divyang Sarathi" posted on the Twitter database. The result shows that the learners are satisfied, but the mobile app usage is less than other e-learning apps like SWAYAM, e-Pathshala etc.
- Twitter sentiment analysis was carried out to analyse the emotions of online users towards mobile apps. It can be inferred from the findings that the awareness level of e-learning mobile apps was more compared to other civics learning apps.
- The simulation results of the study revealed that the cloud-based e-learning system would give the solution for the infrastructure problems. The data centres are deployed, and the performance of the cloud-based e-learning was measured using parameters such as response time, processing time and request service time.
- From the management perspective, single and multiple data centres are deployed, and the values of the parameters are compared. The result of the findings confirmed that the multiple datacenters model is suitable to promote e-learning services.

7.5. Contribution of this Study

This section emphasises the thesis contribution and is separated into three sections, addressing the study contributes to theory, methodology, and practice.

7.5.1. Theoretical Contribution

Policy recommendations

- The e-learning certificate is also considered as a supportive quality of the student. Therefore, the online certificate is considered a part of the academic activities. It would improve the willingness and encourages the users to take part in e-learning.
- In India, it is identified that there is a lack of technology awareness among both genders. Thus, appreciation training and guidance before attending the online is required. Proper training and guidance create technological awareness among students. It also improves the utilisation of online resources. Therefore, the awareness program must be conducted among university students and should be included in the policy framework.
- The attitude and behaviour of the female students should be considered for future

improvement. Special schemes, programs and separate training have to be conducted for female students in India. It would encourage the active participation of female students in the online environment. Thus, the above suggestion motivates female students to take part in e-learning.

- The financial background is considered a critical factor; therefore, some financial support should be given to the female students. Thus, the improvement in the financial scheme in the policy dimension reflects in the e-learning adoption.
- The above changes in the policy dimension will improve e-learning adoption despite gender differences. It may also help to bridge the gender gap in the Human Development Index.

7.5.2. Methodological Contribution

- The sentiment analysis of Twitter data contributes methodologically to the study in identifying factors associated with technological barriers. It also supported the study in understanding the mobile platform such as civics learning apps (#cVIGIL,#Divyang Sarathi,#Agrimarket polarity) and e-learning apps (#SWAYAM,#e-Pathshala,#E-CBSE) has any impact on the e-learning adoption**.**
- The study followed a concurrent convergent mixed methodology with triangulation. This methodology helped in integrating the qualitative and quantitative data findings to identify the e-learning dimensions, which are considered important in improving the proposed e-learning adoption framework for India.

7.5.3. Practical Contribution

- Secondary data analysis revealed that social media influences positively (creating awareness and support) and negatively (spreading user anxiety) on e-learning. So, mobile applications can either improve e-learning adoption or make the learners drop out of the online course.
- It also supported the study in understanding stakeholders' perceptions, including higher education students, special students, online users, special teachers, staff about e-learning systems. However, it can also be used by academicians and course developers as a feedback mechanism that assists them in designing and improving their e-learning system
- Government should encourage universities to provide offline content as an initial step to digital learning. The Government should increase funding facilities to

establish infrastructure in various parts of the country. As an initiative, it provides reliable networks through the NKN scheme. It regulates the digital resources and communication networks in urban and as well as rural areas. In India, urban areas are already well-equipped with digital resources and provide quality education to participants. However, rural areas are suffering from the digital divide due to unequal digital resources and bandwidth allocation.

- Volunteers from urban areas are advised to spread awareness among rural people and motivate them to use digital resources in a proper way. Education institutions should conduct separate training/courses for instructors and encourage them to develop their own digital content according to the needs.
- The higher education institutions must include online courses as a value-added service in the academic curriculum to encourage students and familiarise themselves with recent digital technologies. This will create awareness about digital learning and reduce the individual barriers of the users.

7.6. The Novelty of this Study

According to Philips and Pugh's principles (1994), the originality of this thesis has been discussed, verified, and judged.

Performing empirical studies that have never been done before.

- The present research is exploratory. This study has designed and proposed an e-learning adoption framework that is suitable for the Indian context. This has not been done previously. Secondly, no published articles in this domain are studied through various information system theories and e-learning theories.

Perhaps in a different context, reinterpreting an existing theory

- This study interprets the research questions through different e-learning dimensions and factors such as learner, technology, barrier, design, institution, management and pedagogical dimensions. However, in e-learning, there is a lack of theoretical concept that specifically addresses all these dimensions in a single adoption model. As a result, this study claims novelty in using information system theories models and learning theories to achieve the research objectives.
- Trying something out in this country that's only been done in other countries previously. Although e-learning is not a new domain, the analysis of several e-learning dimensions and the design of an eight-layer architectural framework,

especially for the Indian setting, is novel. This study also considers the novelty in integrating primary and secondary data approaches to design questionnaire surveys and interviews to identify and understand the complexities in the e-learning system in India.

Taking an existing approach and adapting it to a new situation

- The causal loop diagram, which is useful for visualising and understanding interrelationships in the form of causal links (positive and negative) and causal loops (balancing and reinforcement), has been utilised to promote e-learning on mobile and cloud platforms in India.
- Twitter sentiment analysis has been found to be successful in predicting e-learning barriers in the Indian context. The same has been tested for awareness of mobile apps for civic and e-learning. It was found that people are joyous and satisfied with the launch of these mobile applications for both civics and e-learning service.

Adding to the domain of research in a way that hasn't been done before

- The approach for analysing the content of the tweets extracted from Twitter websites and finding out the significance of the components identified will be a novel one for future researchers in e-learning to explore new possibilities in the facets of mobile assist e-learning research.

7.7 Limitations of this Thesis

This thesis has some limitations and scope for improvement for future research. Some of the limitations are listed below:

- The tweets for e-learning barriers and mobile apps were chosen randomly, so they may not be representative and may change over time. This research was carried out only in selected universities, and the future study will add the universities in other parts of India.
- Tweets were classified as 'unknown' among polarity and emotion values during the Twitter sentiment analysis for e-learning barriers and mobile apps. This could be due to the type of lexicon or the use of different writing styles in the tweets, such as @pplications, not good, etc.
- Due to the topic's sensitivity, time, and other financial constraints, difficulties were observed in obtaining targeted interviewees in the qualitative portion of

this study. Furthermore, some respondents are hesitant to provide specific information during the interview procedure, impacting the study's results' credibility.

- Furthermore, because of the participants' fears about confidentiality, interview responses were handwritten, and subsequent data analysis depended on these handwritten notes, which could be limited in such a circumstance.
- Even though measures have been taken to reduce the researcher's bias, his knowledge, background, and experiences may impact research processes such as sample selection, interviewing, and data processing.
- The majority of data responses in the quantitative section of this study were from participants in the south of India, which may be a limitation in generalising the overall population's awareness of e-learning adoption.

7.8 Suggestions for Future Research

This section offers several potential study topics to develop in the future:

- The research also includes a content analysis of tweets for e-learning barriers and mobile apps and an awareness of the primary themes that users are concerned about. On the other hand, this research can be further investigated by classifying the content based on frequency and hashtags for statistical validation and hypothesis testing.
- Mobile assist learning attracts the attention of special students in India. Future research will consider the regulatory framework for special education with various disabilities.
- The research is carried out only in urban areas, so future study includes rural and semiurban areas.
- This study includes only limited mobile apps, and more apps could be considered for future research.
- The e-learning adoption framework can be extended by including course design and instructor dimension to measure its significance.
- The accessibility of digital resources needs to be researched as it has not been embraced in this study.
- The framework adopted in this thesis can be further validated by using qualitative comparative analysis to include more case studies, including learners, teachers and content developers, resulting in more accurate results.

- A cross-country study could benefit by contributing to the literature and by increasing the understanding regarding e-learning adoption among users.

7.9 Conclusion

This research aims to improve e-learning adoption in India. To analyse the relationships between various e-learning dimensions and factors, the study used qualitative (using primary and secondary data) and quantitative (using questionnaire survey) study methodologies. Using various research approaches or mixed methodologies allows for triangulation of study findings for comparison and validation with the overall conceptual framework. This chapter summarises the key findings that led to revisiting and answering the research questions, significant contribution and limitations of the study. Future research directions have been presented to continue the research and to enrich the study domain.

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APPENDIXES

APPENDIX A

QUESTIONNAIRE

NATIONAL INSTITUTE OF TECHNOLOGY KARNATAKA
SCHOOL OF MANAGEMENT

E-learning Adoption

This is regarding a research project undertaken at NIT Karnataka. I am looking for your perception of the existing e-learning service. The survey focuses on the practice of Information and Communication Technologies (ICTs) in the teaching and learning process. The attitude and impact of ICTs towards e-learning are measured using a questionnaire. It consists of basic parameters like course design and structure, ICT infrastructure, pedagogical details and background information about the respondent. It also includes some basic questions about cloud technology in the education sector. It should take no more than 15 minutes to complete the questionnaire – most questions can be answered simply by a tick mark. All responses are anonymised and purely for academic study purposes.

Thank you

VANITHA P S

SECTION -A

Please tick any one applicable

1.	I am familiar with the following online course(s).					
a.	Coursera.	SD [1]	D [2]	N [3]	A [4]	SA[5]
b.	Edx.	[1]	[2]	[3]	[4]	[5]
c.	Udacity	[1]	[2]	[3]	[4]	[5]
d.	Khan Academy.	[1]	[2]	[3]	[4]	[5]
e.	Udemy.	[1]	[2]	[3]	[4]	[5]
f.	Alison.	[1]	[2]	[3]	[4]	[5]
g.	NPTEL	[1]	[2]	[3]	[4]	[5]
h.	Others	[1]	[2]	[3]	[4]	[5]

2.	**Which are the Internet technology you used for most communication?**					
a.	E-mail.	[1]	[2]	[3]	[4]	[5]
b.	Chat.	[1]	[2]	[3]	[4]	[5]
c.	VOIP.	[1]	[2]	[3]	[4]	[5]
d.	Video conference	[1]	[2]	[3]	[4]	[5]
e.	Forum	[1]	[2]	[3]	[4]	[5]
f.	Blogs	[1]	[2]	[3]	[4]	[5]
g.	Other social media	[1]	[2]	[3]	[4]	[5]
3.	**How many hours did you spend to complete the following online course activities?**					
		Less than 10 hrs. [1]	10-15 hrs. [2]	15-20 hrs [3]	20 -25 hrs. [4]	More than 25 hrs.[5]
a.	Forums.	[1]	[2]	[3]	[4]	[5]
b.	Chat rooms.	[1]	[2]	[3]	[4]	[5]
c.	E-mail	[1]	[2]	[3]	[4]	[5]
d.	Video conference.	[1]	[2]	[3]	[4]	[5]
e.	How many hours in a week do you browse over the Internet?	[1]	[2]	[3]	[4]	[5]
f.	On average how many hours in a week do you spent on the online course?	[1]	[2]	[3]	[4]	[5]
4.	System Quality	SD [1]	D [2]	N [3]	A [4]	SA[5]
a.	The online course provides ease of navigation	[1]	[2]	[3]	[4]	[5]
b.	Tools are well-matched to the learning environment	[1]	[2]	[3]	[4]	[5]
c.	E-learning provides the flexible platform	[1]	[2]	[3]	[4]	[5]
5.	Information Quality					
a.	The content sufficiently explains the knowledge, abilities, and ideas.	[1]	[2]	[3]	[4]	[5]
b.	The case studies and scenarios help to understand the concept clearly.	[1]	[2]	[3]	[4]	[5]
c.	The course content is consistent with the objectives.	[1]	[2]	[3]	[4]	[5]
6.	Service Quality					
a.	Availability of the instructor via email or online discussion is satisfied	[1]	[2]	[3]	[4]	[5]
b.	Frequent reply to the student posts in the discussion forum is satisfied.	[1]	[2]	[3]	[4]	[5]
c.	Getting timely reports guided me to handle the course efficiently.	[1]	[2]	[3]	[4]	[5]
7.	Collaborative quality					
a.	It develops collaborative knowledge in the online environment	[1]	[2]	[3]	[4]	[5]
b.	It is comfortable to work in a combined way with others	[1]	[2]	[3]	[4]	[5]

c.	It is easy to communicate and share multimedia information on an e-learning platform	[1]	[2]	[3]	[4]	[5]
8.	Computer self-efficacy					
a.	Know how to map the network drive to link with my web folder	[1]	[2]	[3]	[4]	[5]
b.	Easy to connect and use the Smartboard.	[1]	[2]	[3]	[4]	[5]
c.	Able to integrate multiple technologies	[1]	[2]	[3]	[4]	[5]
d.	Know how to map the network drive to link with my web folder	[1]	[2]	[3]	[4]	[5]
9.	Internet self-efficacy					
a.	I can use the Internet source effectively to practice online test/exercises efficiently.	[1]	[2]	[3]	[4]	[5]
b.	I can use the Internet source effectively to discuss the ideas with instructors and peers in the forum	[1]	[2]	[3]	[4]	[5]
c.	Internet self-efficiency improve self-confidence and performance throughout the course.	[1]	[2]	[3]	[4]	[5]
10.	Learner attitude					
a.	It provides me with an opportunity for self-paced learning	[1]	[2]	[3]	[4]	[5]
b.	It would be easy for me to learn online.	[1]	[2]	[3]	[4]	[5]
c.	It is easy to adapt to the online environment.	[1]	[2]	[3]	[4]	[5]
11.	Learner behavior					
a.	I can browse the course content easily	[1]	[2]	[3]	[4]	[5]
b.	I will answer online questions and interact easily with groups	[1]	[2]	[3]	[4]	[5]
c.	I can able to download the materials and search for references in the forum easily.	[1]	[2]	[3]	[4]	[5]
12.	Learner confidence					
a.	I feel confident to use the Internet for online learning	[1]	[2]	[3]	[4]	[5]
b.	I feel confident to use e-learning tool to share ideas among peers and instructors	[1]	[2]	[3]	[4]	[5]
c.	I feel confident to handle software and network utilises in the online environment.	[1]	[2]	[3]	[4]	[5]
13.	Prior knowledge					
a.	I am familiar with online courses like Coursera, edx, Udacity, NPTEL, etc.…	[1]	[2]	[3]	[4]	[5]
b.	I am familiar with other social media	[1]	[2]	[3]	[4]	[5]
c.	I have attended and completed the online course successfully.	[1]	[2]	[3]	[4]	[5]
14.	Learner characteristics					
a.	The personal learner character helps to enrich the knowledge/skill through self-learning	[1]	[2]	[3]	[4]	[5]
b.	The learners’ social character supports to discuss the topics with other social network groups	[1]	[2]	[3]	[4]	[5]
c.	The learners’ cognitive character improves the learners’ ability in the current working environment	[1]	[2]	[3]	[4]	[5]

15.	Perceived usefulness					
a.	The quality of multimedia used in the course is satisfied.	[1]	[2]	[3]	[4]	[5]
b.	Hypermedia and hypertext improve e-learning platforms.	[1]	[2]	[3]	[4]	[5]
c.	The quality of audio/video used in the course is high	[1]	[2]	[3]	[4]	[5]
d.	The quality of the questions discussed in the group discussion and peer communication is satisfied	[1]	[2]	[3]	[4]	[5]
16.	Perceived satisfaction					
a.	The e-learning access set-up or LMS set-up is adequate.	[1]	[2]	[3]	[4]	[5]
b.	The e-learning platform is clear and structured.	[1]	[2]	[3]	[4]	[5]
c.	The overall satisfaction level of the online course is high.	[1]	[2]	[3]	[4]	[5]
d.	Improves communication skills in the online environment	[1]	[2]	[3]	[4]	[5]
17.	E-learning adoption					
a.	Improves communication skills in the online environment	[1]	[2]	[3]	[4]	[5]
b.	Improve the quality and duration of learning compared to a traditional environment	[1]	[2]	[3]	[4]	[5]
c.	It makes me familiarised with new technologies	[1]	[2]	[3]	[4]	[5]

APPENDIX B

18.	**Lack of ICTs facilities**					
a.	Improves communication skills in the online environment	[1]	[2]	[3]	[4]	[5]
b.	Improve the quality and duration of learning compared to a traditional environment	[1]	[2]	[3]	[4]	[5]
c.	It makes me familiarised with new technologies	[1]	[2]	[3]	[4]	[5]
d. 19.	Lack of Internet facilities					
a.	I feel the Internet connectivity is poor	[1]	[2]	[3]	[4]	[5]
b.	I am not satisfied with the Internet quality	[1]	[2]	[3]	[4]	[5]
c.	The Internet speed is low	[1]	[2]	[3]	[4]	[5]
d.	The cost of Internet is more expensive	[1]	[2]	[3]	[4]	[5]
20.	The discomfort of ICT use					
a.	I am not comfortable with PC and software used in the e-learning course	[1]	[2]	[3]	[4]	[5]
b.	The browsing speed of the Internet is not satisfactory	[1]	[2]	[3]	[4]	[5]
c.	The on-campus Internet connectivity is not reliable	[1]	[2]	[3]	[4]	[5]
d.	Overall, ICTs infrastructure is not sufficient	[1]	[2]	[3]	[4]	[5]
21.	User anxiety					
a.	I am uncomfortable using computers	[1]	[2]	[3]	[4]	[5]
b.	Lack of Internet skill	[1]	[2]	[3]	[4]	[5]

c.	Communication between peers and instructors is more difficult.	[1]	[2]	[3]	[4]	[5]
d.	I am unable to handle the online resources effectively	[1]	[2]	[3]	[4]	[5]
22.	Lack of prior knowledge					
a.	I am not familiar with the use of PC and software applications.	[1]	[2]	[3]	[4]	[5]
b.	Lack of instructor's prior experience in an online course	[1]	[2]	[3]	[4]	[5]
c.	Improper use of the Internet and other online resources	[1]	[2]	[3]	[4]	[5]
23.	Technological barriers					
a.	The quality of audio/video used in the course is low.	[1]	[2]	[3]	[4]	[5]
b.	The technical quality of the course is low.	[1]	[2]	[3]	[4]	[5]
c.	Tools are not matched to learning environments.	[1]	[2]	[3]	[4]	[5]
24.	Individual barriers					
a.	The e-learning platform is not clear	[1]	[2]	[3]	[4]	[5]
b.	Flexibility is not achieved	[1]	[2]	[3]	[4]	[5]
c.	Difficult to navigate through online resources.	[1]	[2]	[3]	[4]	[5]
d.	The e-learning course is not well structured	[1]	[2]	[3]	[4]	[5]
25.	Barrier influencing e-learning adoption					
a.	E-learning tools are not friendly to perform the task.	[1]	[2]	[3]	[4]	[5]
b.	The e-learning access set up or LMS set up is inadequate	[1]	[2]	[3]	[4]	[5]
c.	The overall satisfaction level of the e-learning course is low.	[1]	[2]	[3]	[4]	[5]

Demographic Details

Gender

Male.
Female.

Organisation details

Central Government.
State Government.
Private Institution.
Others.

Employment Status: Are you currently working?

Education sector.
IT field.
Student.
Others.

What is your current grade level?

School.
Bachelor's Degree.
Master's Degree.
Advanced Graduate or PhD.
Not Sure.

Age

Below 17.
18-21.
22 - 25.
26 - 30.
31- 40.

APPENDIX C

Consent Form for Participation in Interview Research

National Institute of Technology Karnataka, Surathkal

I volunteer to participate in a research study conducted by Vanitha P S from NITK Surathkal. I understand that this study is designed to gather information about special education and mobile applications in India.

1. I have been given sufficient information about this research project. The purpose of my participation as an interviewee in this study has been explained to me and is clear.
2. My participation in this interview is voluntary, and I am free to withdraw at any time without giving any reason. In addition, if I am uncomfortable to answer any particular question or questions, I am free to decline or end the interview. If I decline to participate or withdraw from the study, it will not be disclosed.
3. I understand that notes will be written during the interview and the responses will be tape-recorded. The extracts from the interview will be kept as confidential and used only for the academic purpose.
4. I have read and understood the explanation provided to me, I have had all my questions answered to my satisfaction, and I voluntarily agree to participate in this study.

______________________ ______________________

Participant’s Signature Signature of the witness

____

Signature of the Investigator

INTERVIEW QUESTIONS FOR INSTITUTIONS

Name of the Interviewer: Vanitha P S

Name of the Interviewee:

Organisation:

Place of Interview:

Date of Interview:

- Gender:
- Age:
- What is the designation in the institution?
- How many years have you been in this institution?
- What is your highest level of education?
- Organisation details
  [] Central gov. [] State gov. [] Deemed university [] Private institution [] Others
- What is your monthly income?
  [] below 10,000 [] 10,000 -20,000 [] 20,000 – 30,000 [] above 30,000 [] Prefer not to say

Government Factors (GF)	
1.	What all RCI (Rehabilitation Council of India), any other government scheme supported for your institution?
2.	Whether you are getting funds from any government and private organisation?
3.	What are the policies you are following to implement a learning environment for the special students?
Economic Factors (EF)	
4.	What is the annual budget of your organisation? How much do you spend to adopt the assistive technology device annually?
5.	Do you face any financial difficulties to adopt the new assistive technology device?
6.	Whether you are getting special funds by the sponsor to adopt the assistive technology device.
Technology Factors (TF)	
7.	Do you get any free assistive technology devices from standard companies?
8.	Whether students/teachers found mobile applications to help them in learning and teaching? If not, why?
9.	Do you get the device used for teaching?
10.	What are the measures taking place to rectify the technical issues?
11.	Which company provides technical service to your organisation? Whether any special software developed to overcome the previous issues?
12.	Can you describe how m-learning reduces the learning cost of the organisation?

Have I missed anything? Anything you would like to mention.

Interviewee Signature

INTERVIEW QUESTIONS FOR INSTRUCTORS'

Name of the Interviewer: Vanitha P S

Name of the Interviewee:

Organisation:

Place of Interview:

Date of Interview:

- Gender
- Age
- What is the designation in the institution?
- How many years have you been in this institution?
- What is your highest level of education?
- Organisation details
  - [] Central gov. [] State gov. [] Deemed university [] Private institution [] Others
- What is your monthly income?
  - [] below 10,000 [] 10,000 -20,000 [] 20,000 – 30,000 [] above 30,000 [] Prefer not to say

School Factors	
13.	Which syllabus are you following? [] State School Education Board [] NIOS [] ICSE [] IGNOU [] NCERT [] Open Schools of different States and NGOs
14.	Whether any special computer-related courses or training included as a value-added course in the syllabus? If yes, please mention them.
15.	Whether standard e-learning like NPTL/Coursera etc. are helpful in teaching /learning? Materiel
16.	If not, why such large-scale platform services not useful?
Technology Factors	
17.	Mention different types of technologies do you use to teach and communicate with students?
18.	If a mobile device is used as a gadget, then mention the applications currently used to teach?
19.	What are the challenges have you had using computers, and mention any suggestions to overcome them?
20.	Whether the mobile application overcome the challenges and give a solution for computer-related issues?
21.	What are assistive technologies do you use in the teaching-learning process?
22.	Whether the assistive technology helps to use computer technology effectively in your teaching?
23.	Whether you suggest any assistive technology or mobile application that you wish and could use in your teaching?
24.	Do you have any suggestions or recommend any assistive technology or mobile application for the students? If yes, please give your suggestions with examples.
25.	How do you use your presentation software like PowerPoint, Google Slides for your teaching? Whether any additional technical support provided by your organisation?
26.	Who is developing/recommending those applications for teaching?
27.	What are the subjects/areas they using mobile- applications for teaching?
28.	What all mobile platform applications they are used for learning/teaching purposes (request to name five applications like the text to speech, Intel Reader, Draft builder, FM Systems, Sound-Field Systems, sip and puff system, proofreading software, MathTalk, tablets and iPads, E-reader and iPod Touch)
29.	Whether applications form, Google-play can be used directly for teaching/ learning.
30.	Whether the continuous usage of digital gadgets causes any problem for the students? Did you get any complaints from the students?

31.	Can you please give a case example describing how the mobile application overcomes the assistive technology drawback?
32.	Whether mobile technology improves the quality of learning? If so, give some examples.
33.	What are the factors that influence m-learning in special education?
34.	How will it improve their participation level in the collaborative environment? How is it reflected in their everyday life?
35.	How is mobile application/assistive technology influencing individuals in various domains like hobbies, education, and employment?
36.	Can you describe how mobile applications are better than assistive technology in your teaching?
Teacher Factors (TF)	
37.	What helps you use computer/mobile/assistive technologies effectively in your teaching? (Whether you have undergone special training to the professors or experts, owned any personal software, have a high level of motivation or knowledge)
38.	What type of technical workshops or training programs do you want to attend?
39.	If you attended any programs like that? If yes, what aspects of the program do you like or dislike?
40.	Any special training or program related to technology usage that you need to add in the curriculum.
Learner Factors (LF)	
41.	Whether students are aware of social media? If so, how it is related to the learning process?
42.	Whether there are using computers during the learning process? If so, what are the benefits achieved through computers?
43.	When you have a student with different disabilities, what changes do you make use of computer technology?Example, different types of blindness: mild vision loss, mild vision loss, near-total visual impairment and total visual impairment

Have I missed anything? Anything you would like to mention.

INTERVIEW QUESTIONS FOR DIFFERENTLY-ABLED STUDENTS

Name of the Interviewer: Vanitha P S

Name of the Interviewee:

Organisation:

Place of Interview:

Date of Interview:

DEMOGRAPHICS DETAILS:

Please write your responses [ ] tick anyone/more applicable.

- Gender: [] Female [] Male [] others [] Prefer not to say
- Age : [] below 17 [] 18-21 [] 22-25 [] 26-30 [] 31-40 [] above 40
- In which state were you born?
  [] Tamil Nadu [] Karnataka [] Kerala [] Andhra Pradesh [] others
- What is your current grade level?
  [] School [] UG [] PG [] PhD [] Others
- Organization details
  [] Central gov. [] State gov. [] Deemed university [] Private institution [] Others
- What is your parents' monthly income?
  [] below 10,000 [] 10,000 -20,000 [] 20,000 – 30,000 [] above 30,000 [] Prefer not to say

Learner Factors (LF)	
44.	Please mention the category you belong to (you can select more than one) [ ] Blindness [ ] Leprosy Cured persons [ ] Low Vision [ ] Mental Illness [ ] Dwarfism [ ] Locomotor Disability [ ] Intellectual Disability [ ] Cerebral Palsy [ ] Muscular Dystrophy [ ] Acid Attack Victim [ ] Specific Learning Disabilities [ ] Parkinson's disease [ ] Multiple Sclerosis [ ] Thalassemia [ ] Autism Spectrum Disorder [ ] Hemophilia [ ] Sickle cell diseases [ ] Chronic Neurological conditions [ ] Hearing Impairment (Deaf and Hard of Hearing) [ ] Multiple Disabilities including Deaf-Blindness
45.	Students' views towards the web design
46.	Students' views towards the theme of access to the adapted technology
47.	Students' views towards the usage of mobile devices
48.	Students' views towards the products-content of e-education
49.	Students' views towards the high cost of the technological devices
50.	How mobile technology used in your daily activities?
51.	How did it use in your learning activities? Did you find anything mainly improves your learning skill?
52.	Any difficulties faced in the existing mobile learning model? Please provide your suggestions for improvement.
53.	What are the unique features you are looking for in such applications?
54.	How will you relate mobile learning technology to your personal life?
55.	Do you have any other comments to add about your study experience on this module?

Have I missed anything? Anything you would like to mention.

B I O–D A T A

VANITHA P S

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EDUCATION

National Institute of Technology, Surathkal, Karnataka, India
PhD***** June 2021 (Information Systems)

Government College of Technology, Coimbatore, Tamil Nadu
June 2011
Master of Computer Science and Engineering (First Class with Distinction), 76.85 %

Kumaraguru College of Technology, Coimbatore, Tamil Nadu
April 2004
Bachelor of Engineering in Information Technology (First Class), 71.55%

Nanjappa Institute of Technology, Coimbatore, Tamil Nadu
April 2001
Diploma in Computer Science and Technology (First Class with Distinction), 91.08 %

ARC Matriculation School, Coimbatore, Tamil Nadu
April 1998, (First Class), 79.81%

WORK HISTORY

National Institute of Technology (NIT) Surathkal, Karnataka, India
Teaching Assistant (June 2017 - May 2019)

Mahalingam Institute of Technology, Pollachi, Tamil Nadu.
Assistant Professor (June 2015 - May 2016)

National Institute of Technology (NIT) Calicut, Kerala.
Adhoc Lecturer (22nd July 2011 – 19th May 2014)

Government College of Technology, Coimbatore, Tamil Nadu
Teaching Assistant (6th Jan 2010 – 01th May 2011)

Orange Infosys, Tirupur, Tamil Nadu
Software Programmer (1st June 2007 – 30th May 2009)

MPNMJ Engineering College, Erode, Tamil Nadu
Assistant Lecturer (15th June 2005 – May 2007)

PAPER PUBLICATIONS

- Vanitha, P.S., & Alathur, S. (2021) Factors influencing E-learning adoption in India: Learners’ perspective. *Education & Information Technology*. https://doi.org/10.1007/s10639-021-10504
- Vanitha, P. S., & Alathur, S. (2020). E-learning adoption based on gender differences: insight from India. *International Journal of Innovation and Learning*, *28* (4), 510-538.
- Vanitha, P. S., & Alathur, S. (2020). Cloud-Based E-Learning Service: Insight from India. In *ICT Analysis and Applications* (pp. 417-425). Springer, Singapore
- Vanitha, P. S., & Alathur, S. (2019, April). E-learning services: Insights from Twitter Analytics. In *2019 International Conference on Advances in Computing and Communication Engineering (ICACCE)* (pp. 1-6). IEEE.
- Vanitha, P. S., & Alathur, S. (2021). An empirical study on mobile-assisted civic and e-learning service through sentiment analysis. *International Journal of Mobile Learning and Organisation. (Paper Accepted)*

PUBLICATIONS UNDER REVIEW

- Vanitha, P.S., & Alathur, S. (2021). Comparison of Assistive Technology Device and Mobile Assisted Learning in Special Schools: Qualitative Study in India.
- Vanitha, P.S., & Alathur, S. (2021).Learners’ Perception and E-learning Reality: Insights from India.
- Vanitha, P.S., & Alathur, S. (2021). E-learning Adoption Framework – Insights from India

CONFERENCES

- 4 th International Conference on ICT for Sustainable Development (ICT4SD) Co-located with World Publication & Conference Submit. Cloud-based E-learning service: Insight from India July 2019
- 5 th IEEE International Conference on Advances in Computing and Communication Engineering (ICACCE) Bannari Amman Institute of Technology, Tamil Nadu, April 2019

WORKSHOPS

- University of Hyderabad, Hyderabad, Article Writing in Management and Social Sciences, May 2020
- NITTE Justice K S Hedge Institute of Management, Karnataka, Understanding Artificial Intelligence and Design Thinking for Building an Organization of the Future, April 2018.
- Indian Institute of Technology, Bangalore, Machine Learning using R, Dec 2017
- National Institute of Technology, Karnataka, Design Thinking, Nov 201 7
- Indian Institute of Technology, Delhi, Cloud Computing, Feb 2017
- National Institute of Technology, Karnataka, Virtualisation: Foundation to Cloud Computing, Jan 2017

CERTIFICATE OF APPRECIATION

IEEE Software Journal, Reviewer, 2018.

CERTIFIED COURSE

National Institute of Electronics and Information Technology

Calicut, Kerala, Aug 2014 to Feb 2015
PG Diploma Course in Information Security and Cloud Computing, (S Grade).

<u>COMPETITIVE EXAM</u>
Graduate Aptitude Test in Engineering - 2008
GATE SCORE – 161 (All India Rank – 10642)

<u>HONOURS & ACTIVITIES</u>
- Second place in Paper Explorer - National Level Symposium TRANSPIRE-10 at Tamil Nadu Agricultural University Coimbatore," Location-Based System in Agriculture", 20th Dec 2010.
- II Place in Paper presentation in NIS Academy Coimbatore," (Memory Management Techniques", June 2007.

Declaration

I hereby declare that the information furnished above is true to the best of my knowledge.

Yours Sincerely,

[Vanitha P S]