USER ACCEPTANCE, BEHAVIOR INTENTION AND USE BEHAVIOR TOWARDS EDUCATION TECHNOLOGY AMONG EDUCATORS

A Thesis

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DECLARATION

I, Rajesh Dorbala, declare that this thesis has been prepared solely by myself and that it has not been submitted, in whole or in part, in any previous application for a degree. Except where states otherwise by reference or acknowledgement, the work presented is entirely my own.

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ABSTRACT

In the contemporary era of digital transformation, Education Technology (ET) has emerged as a pivotal tool in reshaping higher education, enabling innovative teaching practices, efficient administrative processes, and collaborative research initiatives. Despite its transformative potential, the adoption of ET among educators is characterized by variability and inconsistency, influenced by a myriad of technological, institutional, and individual factors. This study undertakes an in-depth exploration of the determinants of ET acceptance, behavior intention (BI), and actual usage behavior among educators in Central and State Universities in India, grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT). By incorporating novel dimensions to assess post-adoption behavior—namely, Amount of ET Use, Variety of ET Use, and Type of ET Use—this research offers a comprehensive understanding of the multi-faceted dynamics governing ET utilization in academic environments.

Introduction and Research Context

The integration of ET in higher education is no longer optional but essential to meet the evolving needs of students, educators, and the broader academic community. Despite this imperative, educators' attitudes towards ET adoption are influenced by varying levels of access, skill, institutional support, and perceived utility. Recognizing these challenges, this study seeks to address critical gaps in the literature by investigating the factors influencing ET acceptance, the relationship between intention and actual use, and the patterns of post-adoption behavior. The research adopts the UTAUT framework, augmented with constructs designed to capture the depth and breadth of ET application in diverse academic contexts. The focus on Central and State Universities allows for an examination of how institutional types and demographic factors shape ET adoption trends.

Research Objectives and Questions

The study is guided by the following objectives:

1. To investigate the relationship between performance expectancy (PE), perceived enjoyment (PEj), social influence (SI), and effort expectation (EE) of ET and behavior intention (BI)

2. To investigate the relationship between behavior intention (BI) and ET usage.

3. To investigate the relationship between Facilitating Conditions (FC) and ET usage.

4. To examine the moderating influence of University Type and Demographic Variables in the relationship among the antecedents of Behavior Intention (BI), Facilitating Conditions and ET usage.

Methodology

This cross-sectional study was conducted among a stratified sample of 1,000 educators from Central and State Universities across India. A structured survey instrument was developed, incorporating validated UTAUT constructs and additional dimensions for post-adoption behavior. Confirmatory Factor Analysis (CFA) was employed to validate the constructs, ensuring their reliability and internal consistency. Structural Equation Modeling (SEM) was utilized to examine the relationships between constructs, while Multi-Group Analysis (MGA) was applied to explore the moderating effects of demographic and institutional variables. The data was further analyzed to identify usage trends and patterns, offering granular insights into the practical application of ET.

Findings and Insights

Objective 1: To investigate the relationship between performance expectancy (PE), perceived enjoyment (PEj), social influence (SI), and effort expectation (EE) of ET and behavior intention (BI)

- **Performance Expectancy (PE):** Strongly predicted Behavioral Intention (BI), showing educators' belief in ET's ability to enhance teaching, engagement, and efficiency. High PE indicated a strong inclination toward ET adoption.
- **Effort Expectancy (EE):** Ease of use significantly influenced BI, especially for younger educators in State Universities with limited resources.
- **Social Influence (SI):** Institutional culture, collaboration, and leadership shaped BI. Central Universities showed stronger SI due to robust ecosystems.

- **Perceived Enjoyment (PEj):** While not explicitly mentioned, the positive attributes of PE and SI indirectly suggest enjoyment could play a reinforcing role in the adoption decision.

2. **Objective 2: To investigate the relationship between BI and ET usage**
    - **BI to ET Usage:** Facilitating Conditions (FC) translated BI into ET usage. Educators with strong BI and access to resources frequently used ET for teaching, research, and administration. The introduction of "Amount," "Variety," and "Type" of ET Use captured how BI materialized into actual usage.

3. **Objective 3: To investigate the relationship between FC and ET usage**
    - **Facilitating Conditions (FC):** Essential for translating BI into ET usage. State Universities struggled due to resource limitations, while Central Universities had better support for ET adoption.

5. **Objective 4:** To examine the moderating influence of University Type and Demographic Vaariables in the relationship among the antecedents of Behavior Intention (BI), Facilitating Conditions and ET usage.

    - **University Type:** Central Universities provided stronger facilitating conditions and higher performance expectancy, fostering better ET adoption. In contrast, resource constraints increased effort expectancy in State Universities.
    - **Demographic Variables:** Younger educators showed higher adaptability, favoring innovative tools like gamification and VLEs. Female educators demonstrated stronger engagement with collaborative tools, and experienced educators leaned toward administrative and research-focused ET applications.

Implications for Policy and Practice

The study highlights the transformative potential of Educational Technology (ET), emphasizing its rapid adoption during the COVID-19 pandemic. Educational institutions have realized the vast benefits of ET, which has led to a booming industry and numerous emerging startups. ET companies are advised to focus on user interface simplicity, build strong educator communities, and emphasize performance benefits in promotional strategies. Collaboration with educator influencers and tailored pricing strategies can further expand adoption. This approach ensures ET aligns with diverse educator needs, increasing adoption and satisfaction.

The study has valuable implications for academicians and researchers, offering insights into ET adoption in higher education. By expanding the UTAUT framework with dimensions like post-adoption behaviors and addressing disparities between institutional types, it paves the way for future research. Additionally, integrating constructs such as technology anxiety and self-efficacy into the framework enhances understanding of adoption dynamics. This research underscores the importance of equitable resource allocation and its impact on institutional disparities, urging collaboration between academicians and policymakers to drive inclusive educational strategies.

The societal impact of ET is substantial, with the potential to bridge the digital divide, enhance educational equity, and promote lifelong learning. Investments in digital infrastructure and community-level initiatives like training workshops are crucial. ET can also foster global collaboration and understanding through virtual platforms, empowering marginalized groups by making learning flexible and accessible. The study underscores the role of educators as community leaders, whose effective use of ET contributes to societal and economic development by creating skilled, informed citizens.

For policymakers, the study offers a roadmap to promote equitable access to technology, encourage investment in infrastructure, and design targeted training programs. Policymakers are urged to align ET policies with national education goals, establish robust evaluation mechanisms, and incentivize innovation in ET solutions. By reducing resistance to change through awareness campaigns and preparing crisis-resilient education systems, policymakers can ensure sustainable and inclusive digital transformation in education. These strategies enhance global competitiveness, positioning education systems for future challenges and opportunities.

Contributions to Theory and Practice

This research extends the UTAUT framework by introducing constructs for post-adoption behavior, providing a holistic view of ET utilization in higher education. It bridges the gap between theoretical models and practical applications, offering actionable insights for stakeholders to enhance ET integration.

Conclusion and Future Directions

The study highlights the critical role of educators in driving digital transformation in higher education. By identifying the factors influencing ET adoption and addressing post-adoption behavior, this research lays the groundwork for developing targeted strategies to promote equitable and effective ET usage. Future research could explore longitudinal trends in ET adoption, extend the study to private institutions, and investigate cross-cultural variations in ET utilization. Ultimately, this study underscores the need for a systemic and inclusive approach to fostering technology-driven innovation in education.

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The driving force for undertaking this study was my association with the Education Technology Industry for over a decade. During this tenure, I have observed several bottlenecks and barriers which made the actual users reluctant or skeptical about adopting technologies in the field of education. On the other hand, there were a few educators or students, who were extremely passionate about education related technologies and could foresee immense potential in this realm. So, I too was fascinated to observe and study both contrasting phenomenon and always wanted to go deep into the causes which either encouraged or deterred the educators to use or reject education technologies. Covid-19 and the lockdown which followed bolstered my belief in this study as I could see for myself that those who discredited education technologies lapping up all emerging technologies in this field gleefully.

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List of Abbreviations

Abbreviation	Definition
MOOCs	Massive Open Online Courses
HEIs	Higher education institutions
SDGs	Sustainable Development Goals
ICT	Information and Communication Technologies
IS	Information Systems
TAM	Technology Acceptance Model
UTAUT	Unified Theory of Acceptance and Use of Technology
PE	Performance Expectancy
EE	Effort Expectancy
SI	Social Influence
FC	Facilitating Conditions
HM	Hedonic Motivation
PEj	Perceived Enjoyment
BI	Behavior Intention
PU	Perceived Usefulness
PEU	Perceived Ease of Use
SEM	Structural Equation Modeling
PLS – SEM	Partial Least Squares – Structural Equation Modeling
ANOVA	Analysis of Variance
IDT	Innovation Diffusion Theory
MPCU	Model of Personal Computer Utilization
CU	Central University
SU	State University
AU	Amount of ET Usage
LMS	Learning Management System
C-TAM-TPB	Model Combining the Technology Acceptance Model and Theory of Planned Behavior
MGA	Multi Group Analysis
MM	Motivational Models
MPCU	Model of PC Utilization
SCT	Social Cognitive Theory
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action

ET	Education Technology
VU	Variety of ET Usage
TU	Type of Technology Usage
TTF	Task Technology Fit
CFA	Confirmatory Factor Analysis
SCT	Social Cognitive Theory
GDP	Gross Domestic Product
NEP	National Education Policy
ICT	Information and Communication Technology
BYOD	Bring your Own Device
OER	Open Educational Resources
SPOC	Small Private Online Course
VLE	Virtual Learning Environment
WYOD	Wear Your Own Device
m-Learning	Mobile Learning
e-Learning	Electronic Learning
CNCI	Category Normalized Citation Impact
SDT	Self Determination Theory
PIIT	Personal Innovativeness in the field of Information Technology

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CHAPTER-1
INTRODUCTION

1.1 Overview

India is a rapidly liberalizing nation when it comes to educational reforms. India has over 900 universities and over 40,000 institutions of higher education (HIEs). Additionally, several smaller institutions are affiliated with these universities. Additionally, more than 20% of these small institutions enrol fewer than 100 students per year, rendering educational reforms or raising teaching and learning standards economically unviable. By 2030-2032, India is expected to be the world's 3rd larges economy, with a GDP of approximately ten trillion dollars. This economic boost would be fuelled by knowledge resources rather than the country's natural resources. Additional impetus could be generated by the adoption of a new comprehensive "National Education Policy 2020" (NEP-2020). It has a vision to introduce India-centric system that will transform India into a vibrant and equitable knowledge ecosystem by ensuring that all children receive an India-centric, high-quality education.

1.2 What is Education Technology (ET)?

Educational technology is a complex and integrated process, involving people, procedures, ideas, devices, and organization for analyzing problems and devising, implementing, evaluating, and managing solutions to those problems, involved in all aspects of human learning (AECT 1977)

ET signifies the application of digital resources within classroom to facilitate student-centered, collaborative, and independent learning. In today's classrooms, the typical desktop computer has been joined by other technological advancements such as tablets, dynamic online courses, and even robots that can take notes and record lectures for students who are absent. The proliferation of digital resources for teaching and learning has far-reaching effects: Teachers are using machine learning and blockchain tools, as well as ET robots, to grade tests and keep students accountable for homework. Internet of Things (IoT) devices are also being praised for their ability to create digital classrooms for students to access from anywhere, including school, the bus, home, or elsewhere.

A major contributor to ET's success has been its ability to provide scalable, personalised education. Our individuality manifests itself in the variety of approaches we take to education, the dynamics we develop with our peers and instructors, and the level of interest we take in similar topics. Individual differences in learning speed and approach are to be expected and celebrated. The use of technological resources aids educators in designing age- and ability-appropriate lessons and activities that benefit all students' capacity to learn.

And it seems technology in the classroom is here to stay; educators anticipate that it will have a major influence on their practises in the near future. Hence, it is essential to learn how ET might improve the quality of communication, teamwork, and teaching.

1.2.1 Benefits of Education Technology

There are two major stakeholders for ET, i.e., Students and Educators/Teachers. There could be other parties to ET too, but in this section, we will focus on highlighting the benefits of ET for students’ and educators’ perspective only.

1.2.1.A. Benefits of Education Technology for Students

Modern classroom technology encourages students of all ages to work together and welcomes all perspectives. These are five instances in which technological advances in the classroom are having a profound impact on kids' ability to learn.

- **Enhanced Collaboration :** Collaboration in the classroom is facilitated by cloud-enabled tools and tablets(Adiguzel et al., 2023). Children are better prepared to work together to solve difficulties thanks to tablets filled with educational games and online classes(Camilleri, 2024). While doing so, students may use cloud-based applications to share their work, discuss their ideas, and get help from classmates all in one convenient place.
- **Continuous Access to Education:** Pupils have complete access to the digital classroom owing to IoT devices. Students are no longer limited to the hours they spend in the classroom; with access to their coursework from any location, they may do assignments in the comfort of their own homes, on the school bus, or even while travelling between the two(Cevikbas et al., 2023). In addition, a number of applications make it easier for kids to reach out to professors when they have questions or concerns.
- **Flipped Classrooms:** ET tools are reshaping traditional notions of education and classrooms. Traditional classrooms have students sit passively during lectures or assigned reading before sending them home with assignments and projects to complete(Baskara, 2023). Students are now able to hear lectures whenever it is convenient for them and spend class time focusing on group projects thanks to the proliferation of video lectures and learning applications. Students' sense of self-

awareness, creativity, and teamwork are all enhanced by this approach to learning(Chan & Hu, 2023).

- **Customized Educational Opportunities:** Teachers may tailor their lessons to the needs of their individual pupils with the help of ET(Elfeky & Elbyaly, 2024). One of the goals of this approach is to personalise education based on each student's unique set of skills, interests, and capabilities. Video content technologies allow students to study at their own speed, and the ability to rewind and stop lectures is a great asset in ensuring that they completely comprehend the material being presented. Instructors may utilise data to see who is having trouble in class and then tailor their instruction accordingly(Chugh et al., 2023). Educators are increasingly turning to applications that reliably measure general ability rather than depending on stressful assessments to determine academic achievement. When instructors have access to continuous data on their students' progress, they may better tailor lessons to each student's unique needs and utilise the data to prevent or reverse unfavourable patterns (Elfeky and Elbyaly, 2024.).
- **Lessons That Captivate Students' Attention:** These days, a student's attention may be drawn in many directions by a wide variety of tools and other distractions; thus, it's more important than ever to develop lessons that are both interesting and instructive(Lin & Yu, 2023). The ET camp believes that modern technology is the key to save humanity. Technology is being used in innovative ways by students and resultingly this enhances their participation in the classroom. This includes videoconferencing with classrooms across the world, requiring students to submit their homework in the form of videos or podcasts, and even "gamifying" problem-solving(Nesterenko, 2023).

1.2.1.B. Benefits of Education Technology for Educators

Students are not the only group that benefits from educational technology. Teachers believe ET will help them better engage their pupils in the learning process while also freeing up valuable class time. The following are four examples of how technology is helping educators do what they do best: educate.

- **Grading by Computer:** Grading has become a breeze thanks to artificially intelligent tools. Several of these applications use machine learning to evaluate user input and offer grades based on the criteria set out in the assignment(Nesterenko, 2023). Teacher time is saved when these resources are used, especially for objective evaluations. With more time on their hands, teachers may devote more time to planning lessons and working one-on-one with kids who need it most and those who excel academically(Zaman, 2024).

- **Tools for Classroom Management:** It might be challenging to get a big group of students to accomplish anything. Technology in the classroom offers the ability to streamline many processes, including interactions between teachers and students and the management of classroom conduct(Nesterenko, 2023). Apps have been developed to notify parents and students of forthcoming assignments, and students now can monitor disruptions to their overall learning. A less chaotic and more cooperative learning environment may be achieved via the use of classroom management technologies.
- **Classrooms that are paperless:** ET has eliminated the need for a printing budget, paper waste, and long hours at the photocopier. Digitized classrooms provide easier grading, reduce the stress of protecting hundreds of assignment files, and encourage greener pedagogical practices(Nesterenko, 2023).
- **Eliminating Uncertainty:** Teacher after teacher spends endless hours trying to evaluate their pupils' strengths and weaknesses. All of it may be up for grabs after meeting ET. Educators may now choose from a wide variety of resources, including data platforms, applications, and tools, that provide ongoing assessments of their students' strengths and weaknesses(Lin & Yu, 2023). Some technologies that use real-time data can help teachers figure out a student's strengths, weaknesses, and even signs of learning problems, so they can help students before their bad study habits become obvious, which can take months.

1.2.2 Education Technology Platforms

As the ET space evolves, several terms in this domain have evolved as well, and understanding them may be critical to comprehending the ET sphere in its entirety.

1 **Blended Learning:** Blended learning, also called hybrid learning, is a way to teach that combines traditional classroom lessons with online lessons.

2 **BYOD:** Most students own smartphones and laptops, and their enthusiasm for doing so has not waned. Educators are capitalizing on this enthusiasm by incorporating these devices owned by students into their lectures via mid-lecture quizzes or polls. This enables educators to capture their students' instantaneous grasp of a concept.

3 **Flipped Learning:** Flipped learning is a sort of blended learning model through which the educator distributes study material in the form of notes or a video prior to the lecture so that students can go over it and come prepared for the lecture. This model promotes a more in-depth understanding of a concept because the lecture can be used to resolve problems and clear doubts about the course.

4 **MOOCs:** Massive Open Online Courses (MOOCs) are a type of technology-enabled distance education that is open and can be used by anyone with an internet connection. It is quite beneficial for those who have a desire to learn but lack the motivation to enroll in any offline courses. Numerous universities have either integrated MOOCs provided by third parties into their curricula or created their own MOOCs.

5 **OERs:** Open educational resources (OERs) are freely available materials that educators can use and incorporate into their lectures. They can take the form of digital textbooks, videos, podcasts, or even software.

6 **SPOC:** A small private online course (SPOC) aims to address the shortcomings of massive open online courses (MOOCs), which have long been under fire for their low completion rates and high attrition rates. SPOCs are designed for a small group of learners and provide increased educator support, which helps students complete the course. SPOCs, in general, leverage all the advantages of MOOCs, including their online, structured, and personalized nature.

7 **VLE:** A Virtual Learning Environment (VLE) is an online space that is organized by subject and then by level. It serves as a repository for course information, learning materials, and other resources that can be accessed via an institutional login.

8 **WYOD:** Wear your own device (WYOD) is a subset of BYOD that includes smartwatches and virtual reality (VR) headsets. Numerous universities have experimented with virtual reality headsets to deliver vocational and industrial training. The advent of devices such as Google Cardboard has reduced the cost of such technologies.

9 Mobile learning (m-learning), Electronic learning (e-learning), and digital learning (d-learning) are all common synonyms for learning facilitated by technology. The role of e-learning in relation to conventional schooling may be seen either as a supplement or a replacement. Whereas m-learning complements both traditional and online education.

1.2.3 Education Technology: Estimates and Projections

The market size of ET is bound to increase, and it is estimated to hit USD 3.2 billion by 2025 and USD 10.4 billion by 2027. The digitization along with a favorable education policy is propelling the ET growth, but the major growth is concentrated around some large players such as Byju's and Unacademy who proved to be the leaders in fund raising and consolidation. The reality has changed overtime though.

Covid associated lockdowns acted like a nitro-boost for this industry. Indians have always been associating immense value towards education. Indians by nature may make several compromises in other fields such as health or insurance but education is rarely on their negligence list. The new education policy and also in general have propelled changes in the way education is delivered, i.e., rote-based learning to concept-based learning and technology plays a vital role to enable this change. Even the evolving needs of the industry and the hiring trends demand new skill sets and the traditional education systems are not able to provide those emerging skill sets.

To fill this void, several ET companies have emerged which promise to bridge this gap. The evolving online education system is making the equipping the educational institutions to provide these job-related skills to the students. The penetration of internet and smartphones have also enabled students to access education easily and are also empowering them with new skill sets which the conventional education institutions could not provide. Availability of continuous and varied test prep material on ET platforms from the comforts of their home has also made students adopt these technologies at large. Such conducive environment made the ET environment lucrative for mergers and acquisitions as well. This also led to increased hirings of personnel as the ET products started penetrating in the unchartered regions, beyond the big cities. This industry also witnessed increased investments by biggies such as Google and Amazon. The presence of multiple players offering unique solutions opened up avenues for collaborations and synergy. Due to the overstated number of players in the ET industry, mergers and acquisitions have become ubiquitous for the existing players to gain a dominant position. The acquisitions are usually happening for two primary reasons: (1) those new start-ups with promising intellectual capital in the form of content, delivery, integrated hardware or software are getting acquired (2) those new start-ups with a proven business model, market penetration and good reach are getting acquired. Mergers and Acquisitions can be used for either of the two purposes namely (1) to strengthen the existing market position (2) to exit the competition.

1.2.4 Major Mergers and Acquisitions in Education Technology Industry

The significant expenditures made in this industry brought in roughly $2.2 billion in financing in 2020, which is an increase from the $553 million in 2019. Regarding the ET ecosystem, around 4530 ET start-ups exist in India, and surprisingly 435 were established between 2019 and 2020. LearnVern, SkilloVille, Filo, and BeyondSkool were among the significant new businesses that had their starts in the year 2020.

Table-1.1: Major Mergers and Acquisitions in ET since 2019

Acquirer	Acquiree	Value
Byju's	WhiteHat Jr.	$300 million
Byju's	Doubtnut	$100 million
Byju's	LabInApp	$0.5 million
Unacademy	Mastree	$5 million
Unacademy	PrepLadder	$50 million
Unacademy	CodeChef	$0.375 million
Byju's	Osmo	$120 million
StraighterLine	ProSolutions Training	Undisclosed
Cornerstone	Talespin	Undisclosed
Skillshare	Superpeer	Undisclosed
EduNav	Ellucian	Undisclosed
Houghton Mifflin Harcourt	Writable	Undisclosed
iGrad	Financial Fitness Group	Undisclosed
Peterson's	RMC Learning Solutions	Undisclosed
Follett School Solutions	Livingtree	Undisclosed
PowerSchool	Allovue	Undisclosed
Learning Pool	OnScreen	Undisclosed

Instructure	Parchment	$835 million
Discovery Education	DreamBox Learning	Undisclosed
360Learning	eLamp	Undisclosed
PowerSchool	SchoolMessenger	$300 million
Houghton Mifflin Harcourt	NWEA	Undisclosed
Renaissance Learning	GL Education	Undisclosed
Alliant Insurance Services	KnowledgeVine	Undisclosed
Voxy	Fluentify	Undisclosed
Regent	Pearson Online	Undisclosed

It is impossible to argue against the significance of information and communication technology (ICT), to the economic growth of any nation in modern era. The extraordinary changes brought about by advances in ICT in all spheres of human existence, including the educational system, cannot be overlooked. Significant shifts are becoming more obvious due to the advances in technology; electronic learning paradigm could be cited as an example here. Access to resources, services, distant exchanges, and partnerships have led to significant gains in the quality of learning, teaching, accessibility, and efficiency in higher education. These advancements have been brought about by a variety of factors (Hylén, J. 2006). This gave rise to a completely new industry called EdTech (ET). ET can simply be explained as "any forms of teaching and learning that makes use of technology" (Oliver, R. 2000). It is an indubitable fact that the way education is consumed has undergone a sea change.

Development of individual learning trajectories is gaining ground (Dabbagh, N., & Kitsantas, 7 A. 2012). The conceptual goal of today's learners is predetermined by a number of factors, including the rapid pace at which the information society's socioeconomic development is occurring, the rise in social and professional mobility, the dynamic growth of an economy characterised by high levels of uncertainty, the competitiveness and structural changes in the employment of the working population, and so on Borisenkov, D. (2015). This shift in learning needs, habits and preferences resulted in a plethora of innovative solutions, the core of which is ET. There is no denying the impact that technological advancements will have on today's classrooms. According to Borisenkov (2015), self-study, reciprocal learning, and peer learning through social networks are increasingly serving as the foundation for the future of continuous education. A massive open online course (MOOC), a learning management system (LMS), an environment to foster novel forms of education, and a novel ET infrastructure are all vital parts of a modern technology education platform (Konanchuk, 2013). Now in such a scenario, being able to accept technologies available to us has become a necessity rather than a matter of choice. Educators are left with no choice but to integrate technology in their pedagogy in order to better prepare the students in this information age. According to Twigg (1993), if we forecast a future in which more students will need more education, there is only one way to meet that demand without diminishing the quality of the educational experience that students receive: we must change the manner that we provide education.

Internet revolution hit the universities much faster than it was anticipated. Computer labs and laptops became ubiquitous in the campuses. This has both generated interest and drawn ire at the same time. Institutions are facing this ever-growing challenge of upgrading their technological infrastructure which becomes obsolete quite frequently and also to upskill their faculty pool with every latest technological innovation within their limited budgets. Existing body of research corroborates the fact that faculty has always shown lukewarm response compared to the management's enthusiasm to adopt and integrate technology to meet the expectations of the society and students(Chugh et al., 2023; Duha Khalid Abdul-Rahman Al-Malah et al., 2023; Nesterenko, 2023). Understanding the inherent barriers towards adoption and integration of technology in instruction is also a popular field of study.

It has been found that there would be less resistance towards any kind of innovation if that innovation can be tried before adopting. Such innovation must also be in sync with the personal and professional goals of the educators besides its simplicity. Such innovation must also provide the educators with an upper hand that is to say that it should elevate the educators from the status quo. Moreover, it should also pose some benefits in order not to be meted out with resistance. The adoption of any technology and how it is used in the later stages by an individual or a group and the ensuing perceptions about it dictates the eventual use or nonuse of that technology. But the last two decades have witnessed unprecedented growth in the use of internet and computers for pedagogical purposes. Despite such large-scale adoption, most of it has been non-voluntary, where the management of institutions have enforced the adoption irrespective of the rank and file of the staff (Park et al., 2008). In such situations, there is a high degree of variance in the attitudes and motivations among the educators and this leads to a variance in the degree to which they welcome the novel technologies. Bandura (1977) tried to explain such variance and proposed a construct "Self-Efficacy". An individual's beliefs about his/her competency shapes his/her attitude for the efficaciousness of that technology. Those educators with superlative self-efficacy will have a greater tendency to adopt and subsequently use the technology in question. Self-efficacy has found its mention in a large corpus of literature on technology adoption.

We have come a long way from the bulky desktops to a myriad of devices which are finding their place in education and pedagogy. Technology is no way separable from our lives and education is no exception. Technology is shaping the future of the knowledge society and it is shaping our lives in every possible and conceivable manner. Similar to various other facets of modern life, education has not been left untouched by ever-evolving technology. A sneak peek into the history reveals that for over four decades, information technology has shaped the structure of schools and universities and information technologies are omnipresent in the campuses. With technology making a distinct place for itself in the university campuses, the adoption and subsequent integration into the pedagogy by educators in an effective manner becomes overwhelmingly crucial (Green & Gilbert, 1995). In fact, the survival of institutions of higher education highly depends on to what extent the educators are motivated to adopt and integrate technology in their classrooms (Hagenson, 2001). To make this happen, there needs to be a deep-rooted appreciation for the factors which affect the adoption of technology by educators.

The current study aims to understand the antecedents to Behavior Intention (BI) of the educators in Central and State Universities in India. Subsequent to adoption, the present study would also like to understand the post-adoption phase, that is the actual use behavior of ET, namely how and to what extent this technology will be integrated in the classrooms and the pedagogy. The current study is grounded in the UTAUT (Venkatesh et.al, 2003). UTAUT attempts to explain the predictors of BI to use ET and subsequent ET usage behavior.

1.3 Impact of COVID-19 on Education Technology

Due to widespread lockdowns during this pandemic, educational institutions were forced to devise quick-fix solutions to introduce remote learning, with education technology serving as the lone panacea. The closure of educational institutions as a result of lockdown created an urgent need for technological solutions to upgrade their infrastructure in order to continue providing education uninterruptedly. As a quick fix, educational institutions began relying on third-party video conferencing (VC) apps such as Google Meet, Zoom, Webex, and Microsoft

Teams, as well as ET companies such as Byju's, Unacademy, Vedantu, and TCYOnline, to facilitate the transition from offline to online teaching and learning.

The fundamental premise of various teaching and learning theories was pushed to the side, while education delivery received undivided attention. This could be interpreted as a reflexive response to the collective response to pervasive fear and uncertainty. Educators and learners have been put under enormous social and psychological stress during these times of uncertainty and imposed lockdowns. Inequalities in social and economic status have been exposed, and perhaps all stakeholders in society started thinking of the social importance of education. ET received a boost because of the NEP that was implemented by the Ministry of HRD for the fiscal year 2020-21. The NEP acknowledges that technology is important in the provision of high-quality education. Besides, the NEP suggests the establishment of an independent body that will be known as the National Education Technology Forum. This body will function as a forum for brainstorming ideas pertaining to using technology to learn, improve assessment, planning, and administration. In addition, there have been requests for investments in digital infrastructure, such as teaching platforms, virtual laboratories, and evaluation tools, which, if effectively implemented, might result in large expenditure by the public sector. Additionally, the NEP deliberated on providing teacher training in order to develop high-quality learning digital content and online assignments, as well as design and establish a paradigm for online teaching-learning content and pedagogy. Additionally, the NEP has proposed including coding as a required skill in school curricula, which brought coding platforms such as WhiteHat Jr., Coding Ninja, HackerKid, and Yekie to limelight.

Overnight, all educators worldwide took collective action, relocating their lectures from classrooms, lecture theatres, and laboratories to digital platforms. Perhaps this situation has also created a new market for the numerous ET companies that have sprouted up across the country. While this pandemic may have accelerated ET acceptance, the extent to which this was voluntary or forced is always debatable. Is there genuine educator appreciation for ET? Do they have a favorable view of ET? Do educators intend to discover novel applications for ET and to incorporate it into a variety of scenarios? Numerous studies have been conducted in the past to address these and other related issues. It is critical to examine the circumstances surrounding one's acceptance of technology and the timeframe in which such adoption occurs. And, as technology literacy becomes more ingrained in curricula at all levels of education, acceptance and adoption of ET becomes a requirement rather than a choice (Barron, Kemker, Harmes, & Kalaydijian, 2003).

Higher education institutions are confronted with increased societal expectations, and technology as a skill has become an integral part of the overall educational experience. Even in such times, there is a schism in society at large, and among educators in particular, regarding the efficacy of ET. One school of thought asserts that there is little difference between education imparted via technology and education imparted without technology(Khalid and Al-Malah et al., 2023; Nesterenko, 2023). ET proponents assert that integrating technology into education makes it more accessible, affordable, and effective. Regardless of this disagreement, technology adoption is accelerating in higher education. Technology integration into instruction has become indispensable. However, the implementation of technology-enhanced education in institutions of higher education does not always guarantee successful integration. Though the integration of technology into the curriculum is a matter for the institution's higher authorities, the individual's proclivity for technology adoption is critical in determining whether or not this integration is successful(Elfeky and Elbyaly, ; Zaman, 2024). As a result, it becomes necessary to investigate certain facets, such as why some educators embrace technology with gusto while others abstain. What effect does the social context have on an educator's decision to accept or reject ET? Numerous theories of innovation diffusion have attempted to delve deeply into such issues. All in all, the emphasis should be on integrating technology into the curriculum in order to increase the overall effectiveness of academic instruction, not on jumping on the bandwagon out of fear of missing out (FOMO) on this emerging fad.

Despite the widespread doom that has engulfed all industries during this pandemic, one industry that is thriving is the Education Technology sector. A joint report by Neilson and BARC India claims that the screen time on education applications has increased by 30% since lockdown. This industry, which previously moved at a snail's pace, has suddenly accelerated. It is growing at a breakneck pace. Not only the present, but also the future appears to be bright and shiny, with new avenues opening up and user acceptance of Education Technology increasing. Not only have established players seen unprecedented demand, but this industry has also seen the emergence of several new players who are expected to remain for the foreseeable future. This could be considered the initial wave of digitization, and when combined with favorable education policy, the ET industry continues to grow rapidly. This sector received additional investments and was the epicenter of consolidation activity throughout the fiscal year.

According to Investopedia, Education Technology (ET) is a term that refers to hardware and software that assist educators in enhancing educator-led learning in classrooms and improving students' educational outcomes. The developers and creators of ET extol the virtues of ET in freeing educators from routine tasks and allowing them to focus on assuming a facilitator role. ET holds the promise of enhancing and promoting student and class outcomes. Technology integration in the classroom could be studied in two stages. The first step is to integrate hardware, which may include smart boards, audio visual aids, computers, and tablets. The second phase of integration is software integration, the majority of which are cloud-based and rely on educational research to develop and deploy algorithms that determine the level and speed with which students achieve their learning objectives.

The majority of available ET currently operates in a read-and-respond mode, which disadvantages other types of learners such as auditory and kinaesthetic learners. While ET currently places a premium on individualized learning, educators and parents believe that social and group learning are also critical components of education, and that ET lags behind in this area. Proponents of ET continue to emphasize that while critics may have valid points, ET is intended to supplement rather than replace existing educational models.

1.4 National Education Policy (NEP) 2020

The new NEP 2020, implemented during the COVID-19 pandemic, also ushered in widespread adoption of online education and ET. The NEP 2020 underscored the significance of using ET and ICT in education and called it the “need of the hour”. It is said the ET has the power to bridge the digital divide and can penetrate every nook of the country by delivering education with quality and speed. NEP 2020 also stresses the use of ET to allow everyone to avail themselves of opportunities, with improved quality of education, inclusion and appreciating and respecting diversity across the country. The use of ET can liberate the country with several festooning problems such as unemployment and poverty. The NEP 2020 has laid down a path on how to move forward with Online and technology-enabled education and the same can be summarized through the visual presented below.

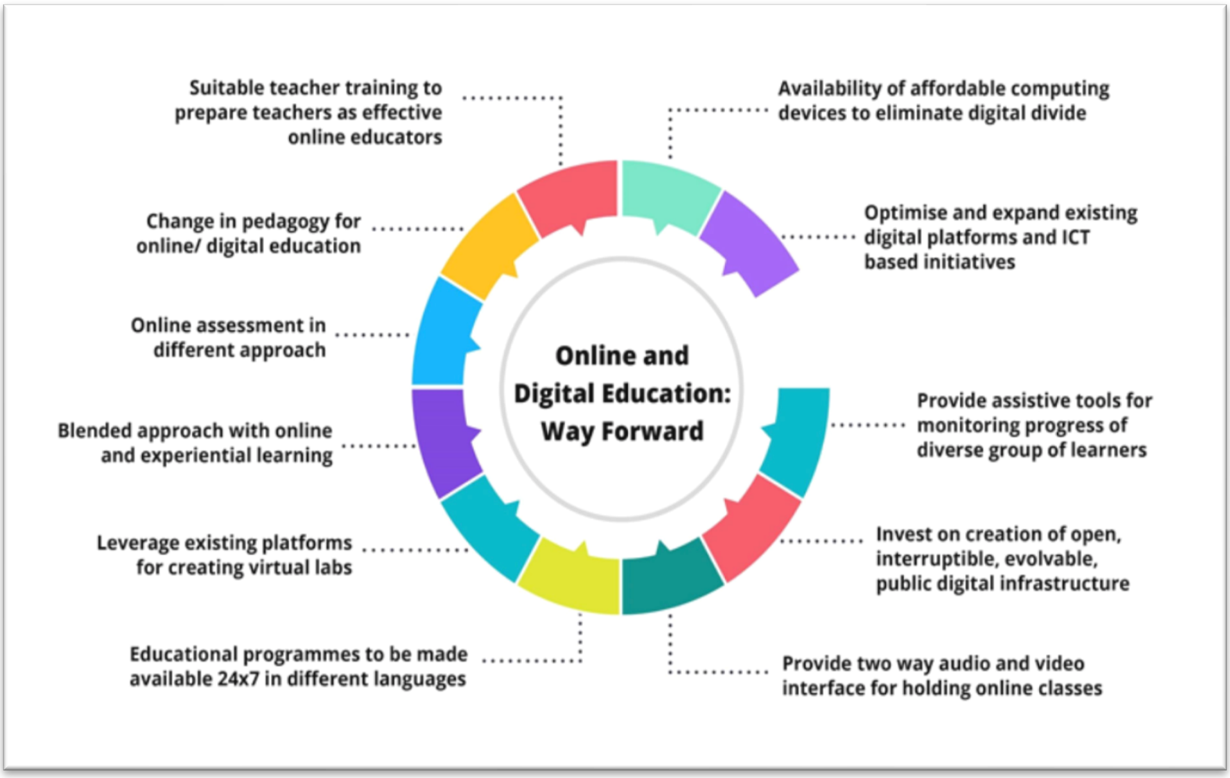

Figure 1.1 Online and Digital Education: Way Forward

Source: (Nesterenko, 2023)

NEP-2020 has also identified several thrust areas which are essential to be focussed upon to improve the quality and delivery of education with inclusivity. The policy emphasizes the importance of using technology to improve the quality, efficiency, and inclusivity of education in India. The thrust areas are summarized as follows:

- **Teaching-learning and evaluation processes:** This could involve using technology for things like online learning platforms, educational games, and adaptive assessments.
- **Supporting teacher preparation and professional development:** Technology can be used to provide teachers with online training courses, professional development resources, and collaboration tools.
- **Enhancing educational access:** Technology can be used to provide educational opportunities to students in remote areas, students with disabilities, and other students who may not be able to attend traditional schools.
- **Streamlining educational management and administration:** Technology can be used to automate administrative tasks, such as grading, record-keeping, and communication with parents.
- **Removing Language Barriers:** The image likely highlights the use of technology to remove language barriers in education through:

- ○ ***Machine translation tools:*** These tools can be used to translate educational materials into different languages, making them accessible to students who do not speak the language of instruction.
- ○ ***Multilingual learning platforms:*** These platforms can provide students with access to educational content in their native language as well as other languages they are learning.
- ○ ***Speech recognition and text-to-speech tools:*** These tools can help students who have difficulty reading or writing to access educational content.

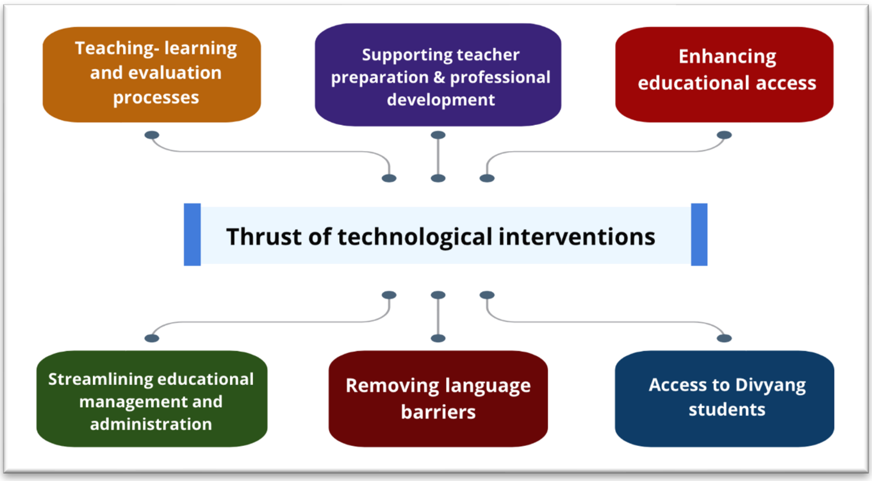

Fig 1.2: Thrust of Technological Interventions

Source: https://www.education.gov.in/

- **Enhancing Access to Divyang Students (Students with Disabilities):**
  - ○ ***Assistive technologies:*** These technologies can include screen readers, speech recognition software, and other tools that can help students with disabilities access and interact with educational content.
  - ○ ***E-learning platforms with accessibility features:*** These platforms can include features such as closed captions, transcripts, and adjustable text size and font to make them more accessible to students with disabilities.
  - ○ ***Online learning environments:*** Online learning environments can provide students with disabilities with more flexibility and control over their learning pace and environment.

By incorporating these technological solutions, the National Education Policy 2020 aims to create a more inclusive education system that caters to the needs of all learners, regardless of their language background or disability status. The National Education Policy 2020 recognizes that technology is a powerful tool that can be used to improve education for all students. The policy calls for increased investment in educational technology and for the development of new and innovative ways to use technology in the classroom.

The use of technology in education is still in its early stages, but it has the potential to revolutionize the way we teach and learn. The National Education Policy 2020 provides a roadmap for using technology to create a more equitable and effective education system for all students in India.

NEP 2020 also presents a futuristic view towards incorporating technology and has laid down a framework towards the adoption of emerging technologies into the education system.

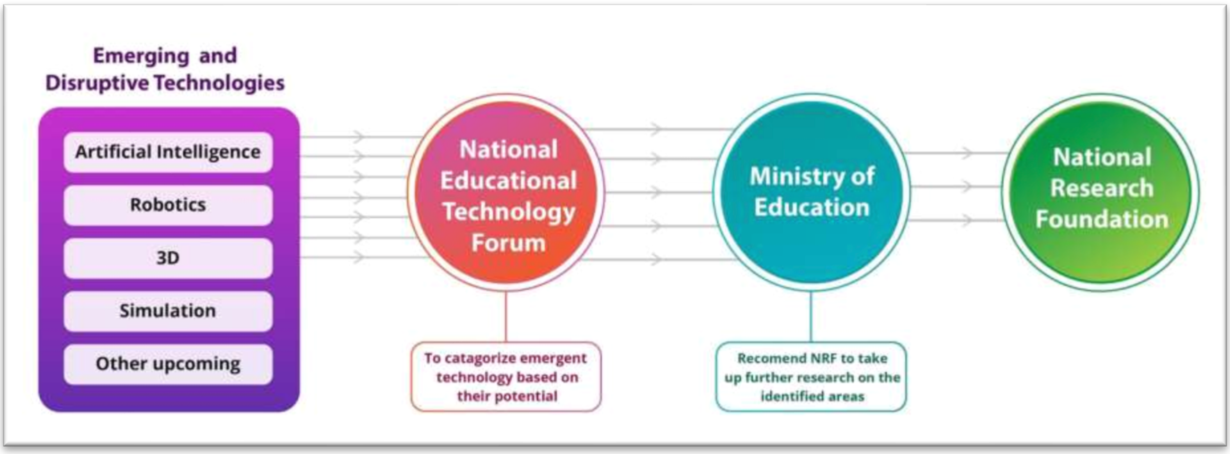

Fig 1.3: Framework Towards Adoption of Emerging Technologies

Source: https://www.education.gov.in/

Here the NEP 2020 has also laid down the roles and responsibilities of the Higher Educational institutions and they are as follows:

- Play an active role in conducting research on disruption versions of instructional materials courses, including online courses and assessing their impact on specific areas.
- HEIs will conduct targeted training for job readiness and address skilling, deskilling and scaling keeping in view the disruptive technologies.

- Universities will aim to offer Ph.D. and Masters Programmes in core areas such as machine learning as well as multidisciplinary fields “AI+X” and professional areas like healthcare, agriculture, and law.

In the context of the rapidly evolving educational landscape, it is imperative to conduct an in-depth investigation into the factors influencing user acceptance behavior, behavioral intentions, and actual usage patterns of Education Technology (ET) among educators in Higher Educational Institutions. Such a study would provide valuable insights into the determinants of ET adoption, the barriers impeding its widespread use, and the behavioral trends among educators. These findings could significantly contribute to the realization of the National Education Policy's (NEP) vision by facilitating the effective integration of technology in the educational process.

CHAPTER-2
REVIEW OF LITERATURE

2.1 Introduction

This chapter looks at theories and models and evaluates relevant literature to unearth factors that might affect the use of ET. It starts by looking at the UTAUT and other models for how people adopt technology. The forthcoming sections review the theoretical background in the information systems fields to find other potential criteria such as perceived enjoyment, amount of education technology use, variety of education technology use, and type of education technology use. This chapter finishes with a review of the lacunae in the literature addressed by the current study and the framing of research topics. A complete and thorough Bibliometric Analysis was performed using R Biblioshiny. To perform this analysis, "bibliometrix" package in R was installed. This analysis is instrumental and useful in understanding the authorities in this field of study and also helps in identifying the noteworthy publications on which the literature review of the current study could be grounded. This renders a scientific approach to the methodology towards developing the literature for this study.

2.2 Literature on UTAUT

The integration of technology in educational practices has revolutionized teaching and learning processes across the globe. By enabling flexibility, collaboration, and access to resources, various digital tools have enhanced educational effectiveness, especially in higher education and K-12 settings. However, the success of these technological implementations largely depends on the extent to which educators adopt and effectively utilize these tools. The **Unified Theory of Acceptance and Use of Technology (UTAUT)** framework offers a comprehensive lens to understand the factors influencing technology acceptance and usage in education. This review discusses how educators use various technologies and provides a detailed exploration of the UTAUT constructs—**performance expectancy**, **effort expectancy**, **social influence**, and **facilitating conditions**—while reflecting on additional moderating factors influencing adoption.

To suit the research needs in adoption and use of new technologies, several academicians have throughout time generated several expansions to this UTAUT core model. Performance Expectancy, Effort Expectancy, Social Influence, Habit, Hedonic Motivation/Perceived

Enjoyment, Facilitating Conditions, Trust, Price Value, Innovativeness, Anxiety, Attitude, and Perceived Risk are the primary factors in the UTAUT model, along with the extended variables.

UTAUT is used in a variety of fields, including educational institutions, such as schools and universities (Liao et al. 2004; Pynoo et al. 2011), academic societies (Gruzd et al. 2012), government agencies (Gupta et al. 2008; Al-Shafi et al. 2009), and medical institutions and hospitals (Gupta et al. 2008; Chang et al., 2007; Alapetite et al. 2009). Not only were these businesses scattered throughout multiple industries, but also over multiple countries and geographic regions, including Asia, and the United States. Students, professors, government leaders, and physicians were among the users. Many different types of technology have been studied by academics: tablet PCs (Garfield, 2005; El-Gayar et al., 2007); e-government services (Al-Shafi et al., 2009); clinical decision support systems (Chang et al., 2007); social media (Gruzd et al., 2012) and interactive learning systems (Liao et al., 2004; Pynoo et al., 2011). Timeliness of UTAUT implementations often hinged on whether users choose to utilize them. Nevertheless, only Pynoo et al., (2011) stayed true to the UTAUT paradigm and investigated the three stages of technology adoption (i.e., consumer acceptance, first use, and post-adoption). Alapetite et al. (2009), however, contrasted accomplishment requirements, engagement expectations, social impact, and pre- and post-accession conditions. By contrast, the majority of UTAUT implementations focused exclusively on the primary effects. Several research have examined the moderating effects of the individual variations identified in the original UTAUT. In general, only a few research have examined the effect of care when examining the usage of technology in existing UTAUT applications.

UTAUT has been included into studies examining the dissemination and use of technology as well as other relevant issues in the scientific community. For instance, in 2012, Yoo et al. looked at how intrinsic and extrinsic motivation affected workers' plans to utilise on-the-job and online training. They articulated performance expectancy, social pressures, and facilitation of situations as extrinsic motivation aspects, as well as commitment expectations as an intrinsic part of internal motivation. Guo & Barnes (2011) analyzed customer purchasing behavior in the virtual world using the same theoretical framework but interpreted performance and engagement expectations as ingredients of Extrinsic Motivation.

Educators have increasingly embraced a wide spectrum of digital tools to enrich the teaching process. These include **learning management systems (LMS)**, **collaborative tools**, **social**

media, **mobile learning apps**, and **specialized subject-specific software** (Bandoh et al., 2024). Each category of technology serves unique pedagogical needs:

- **Learning Management Systems (LMS):** Platforms like Moodle, Blackboard, and Canvas provide a centralized space for educators to share course materials, host discussions, and manage assignments (Bayaga & Madimabe, 2023). LMS usage facilitates streamlined communication, access to learning resources, and tracking of student progress (Chugh et al., 2023).

- **Social Media Platforms:** Social media tools such as YouTube, WhatsApp, and Twitter have found increasing utility in education (Chugh et al., 2023; Da Silva Soares et al., 2024). For example, YouTube offers vast repositories of video tutorials, while WhatsApp enables instant communication among students and instructors. These tools are not just convenient but also foster informal, collaborative, and flexible learning.

- **Interactive and Collaborative Tools:** Tools such as Google Docs, Microsoft Teams, and Zoom have become indispensable for synchronous and asynchronous collaboration (Da Silva Soares et al., 2024; Duan, 2024). These platforms allow teachers to deliver real-time lectures, assign group projects, and foster discussions in virtual settings.

- **Mobile Learning Apps:** Applications like Quizlet, Kahoot, and Duolingo cater to specific learning objectives, making teaching engaging and interactive (Da Silva Soares et al., 2024; Duan, 2024). For instance, Duolingo aids language acquisition, while Kahoot gamifies classroom quizzes, increasing student engagement.

However, technology adoption does not occur in a vacuum. Educators' readiness to utilize these tools is influenced by several factors that align with the constructs of the UTAUT model. The UTAUT framework provides an effective model to understand why educators adopt or resist technology. The following sections detail the core constructs of the model and their application in the educational context.

2.3 Study Development

2.3.1. Developing Constructs for the Current Study

This study is based upon the constructs identified under UTAUT model. Venkatesh et al. (2003) proposed 4 exogenous variables of UTAUT—Performance Expectancy (PE), Social Influence (SI), Effort Expectancy (EE), and Facilitating Conditions (FC) as its components. The UTAUT model has been updated regularly as per the context and requirement of numerous scholars e.g. addition of other constructs such as (Bayaga and Madimabe, 2023) and moderating effects are been witnessed in several studies (Da Silva Soares et al., 2024).

UTAUT Model considers Performance Expectancy (PE), Social Influence (SI), Effort Expectancy (EE), and Facilitating Conditions (FC) as its base components.

The term **Performance Expectancy (PE)** is the belief that using technology will lead to professional growth among workers (Shin, 2009; Davis et al., 1992). As per Compeau & Higgins (1995), the philosophical import of this factor is derived from the following: intrinsic motivation (Motivation Model), relative advantage (Innovation Diffusion Theory), value perceptions (Technology Acceptance Model), job fit (PC Utilization Model), and outcome expectations from "Innovation Diffusion Theory" and "Social Cognitive Theory". In each of the studied models, factors related to PE were the strongest predictors of future adoption of the technology in study. In education, performance expectancy directly impacts technology adoption as educators are more likely to adopt tools that they perceive will improve student outcomes and teaching efficiency (Duman & Oğuz, n.d.; Man & Zainuddin, 2024). Studies have consistently highlighted that tools such as LMS, YouTube, and Google Classroom are widely accepted because they allow educators to:

- Deliver high-quality teaching materials, such as videos and interactive modules, that enhance students' learning experience (Plageras et al., 2023) .
- Simplify repetitive tasks like attendance tracking, grading, and content organization, thereby allowing more time for teaching ("Using the UTAUT Model to Understand Social Media's Adoption for Enhancing Academic Performance among Indian University Students.," 2024).

- Boost student engagement by incorporating multimedia content, which is particularly effective for subjects requiring visual learning, such as science and mathematics (Yuniarty et al., 2024).

For instance, a study found that teachers perceived YouTube as a valuable platform because it provided access to video tutorials that could be integrated into lessons to explain complex topics (Plageras et al., 2023). This aligns with the broader narrative of performance expectancy as educators adopt technologies that promise tangible improvements in classroom delivery.

The term **Effort Expectancy (EE)** was coined at UTAUT to describe the relative simplicity of a given technological solution (Venkatesh et al. 2003). This component was used to create the suggested Perceived Ease of Use as a factor in “Technology Acceptance Model”. Davis (1989) found that the success rate of a system increased when it was easier to use. In recent research by Davis et al. (1989) suggests that, at the beginning of the adoption of a novel behavior, when process difficulties provide challenges to be met, effort-oriented systems are more likely to predominate than queries concerning instrumentality. All of this lines up with the research of Davis (1989), Davis and Venkatesh (2000), and Diaz and Loraas (2005). The degree to which a client thinks that key opinion leaders value technology usage (Diaz & Loraas, 2010), TAM 2 is a follow-up to TAM that includes a "subjective norm" component similar to this one. Benbasat and Moore (1991) provided a definition of "identification" as the degree to which people see technological progress as enhancing their status in society. Despite their seemingly dissimilar names, subjective norm and image both incorporate the idea that one's conduct is affected by how others see them in light of the technology in use. Teachers are more inclined to use tools they find intuitive and require minimal training. For example:

- Social media platforms like WhatsApp are popular because they are familiar, easy to navigate, and require no significant technical expertise (Plageras et al., 2023).

- Tools with minimal technical barriers, such as Kahoot or Google Forms, allow educators to create quizzes or surveys quickly, reducing workload (Pan & He, 2024).

However, effort expectancy often varies based on external factors, such as access to professional training and prior experience with technology (Plageras et al., 2023). Research indicates that a lack of user-friendly design or inadequate technical support can dissuade educators from fully utilizing digital tools, even if they recognize their potential benefits (Plageras et al., 2023). For instance, complex LMS platforms might remain underutilized if teachers do not receive adequate training on features like grade book configuration or analytics tracking (Ravichandran & Shanmugam, 2024).

The role of peers, administrators, and institutional culture significantly influences educators' decisions to adopt technology (Setiasih et al., 2023). **Social influence (SI)** in educational settings manifests in several ways:

- **Peer Influence:** Teachers often look to their colleagues for recommendations or demonstrations of new tools. Observing successful integration of technology by peers encourages others to adopt similar practices (Patil & Undale, 2023).

- **Administrative Policies:** Institutional mandates or recommendations to adopt specific platforms, such as LMS or interactive whiteboards, shape educators' willingness to comply (Karakoyun & Başaran, 2024).

- **Student Expectations:** Increasingly, students expect educators to use digital tools that align with their tech-savvy learning habits. For instance, students might encourage teachers to use multimedia tools like Canva for creating visually engaging materials (Patil & Undale, 2023).

Social influence is particularly evident in collaborative learning environments. Studies reveal that teachers who feel encouraged by peers or supervisors are more likely to integrate innovative tools into their pedagogy (Duman & Oğuz, 2023).

Facilitating Conditions (FC) refer to a person's confidence in the presence of an organizational and technical infrastructure capable of enabling technology usage. A specific topic is covered in Thompson et al (1991), personal computer utilization model. The fundamental facilitation state is intended to include components of a technical and organizational environment with the goal of removing potential roadblocks to the adoption of the system (Keong et al., 2012). UTAUT objects are built on a foundation of assumed action control. The company's efforts to remove usability issues are predicted to increase the likelihood that interested customers would utilize the product.

The Unified Theory of Acceptance and Use of Technology (UTAUT) model, and its subsequent extension to UTAUT 2, have been widely used to analyze user behavior in adopting technology. UTAUT 2 expands upon the original framework by incorporating constructs like perceived enjoyment (PEj) / hedonic motivation (HM), which captures the enjoyment and pleasure derived from using technology. While the model has effectively captured utilitarian aspects like performance and effort expectancy, research highlights the growing importance of addressing intrinsic motivators. Hedonic motivation, as an intrinsic driver, particularly gains relevance in contexts where technology adoption is influenced by personal gratification or emotional engagement, such as open educational practices or consumer-focused technologies. Introducing HM as a construct thus allows for a richer understanding of technology acceptance in scenarios beyond utility and functionality.

A **hedonic motive (HM)** or **perceived enjoyment (PEj)** is one that is driven by a desire to experience the joy or satisfaction that comes from making use of technological tools. It has been shown to have a significant part in determining the acceptance and use of technology (Brown & Venkatesh 2005). The role of pleasurable sensations as a motivating factor has been shown in the study of information systems that the degree of enjoyment that a person derives from utilizing a particular technology is a significant factor in determining whether they would embrace and directly use that technology. In addition to this, it has been shown that hedonic incentive is a key factor in both the growth of markets and the adoption of new technologies (e.g., Brown and Venkatesh 2005; Childers et al. 2001). As a result, “Perceived Enjoyment” or “Hedonic Motivation” is taken into consideration as a possible indication of the consumers' future behavior about the use of technology.

A fundamental distinction between establishing consumer usage and establishing the corporate manner under which UTAUT was founded is that customers typically suffer the financial expense of such consumption, whilst employees do not. The pricing and price structure of a technology can have a significant impact on how customers use it.

Consumers are to be provided with variety as a result of technological advancements. They take the technology that consumers desire and are interested in learning more about the changes that may occur with that technology.

In the current study, the core constructs of UTAUT are adopted along with a construct from UTAUT 2 and the constructs are:

- Performance Expectancy (PE)
- Effort Expectancy (EE)
- Social Influence (SI)

- Perceived Enjoyment (PEj) or Hedonic Motivation (HM)
- Facilitating Conditions (FC)
- Behavior Intention (BI)
- Use Behavior:
    - Amount of ET Use (AU)
    - Variety of ET Use (VU)
    - Type of ET Use (TU)

Further, the study also uses moderators namely:

- Age
- Gender
- Experience
- University Type

The theoretical base of each construct is discussed in detail.

i. Performance Expectancy (PE)

How certain a person feels that incorporating a new procedure into their routine will provide positive results is one measure of the PE construct. Hence, this research hypothesises that everyone involved in the classroom stands to gain from using ET. C-TAM-TPB (Combined Theory of Technology Acceptance Model and Theory of Planned Behavior) and TAM/TAM2, job-fit Model of Personal Computer Utilization(MPCU), extrinsic motivation (from Motivation Models), relative advantage (Innovation Diffusion Theory), and outcome expectancies (OE) were all rolled into a single construct called PE as proposed in the following literature: Usefulness and extrinsic motivation (Davis et al., 1989, 1992); usefulness and relative advantage (Davis et al., 1989; Benbasat & Moore 1991; Plouffe et al., 2001); usefulness and job fit (Thompson et al., 1991); usefulness and outcome expectations (Moore & Benbasat 1991; Davis et al., 1989; Plouffe et al., 2001); (Higgins & Compeau1995b).

Performance Expectancy (PE), a key construct of the Unified Theory of Acceptance and Use of Technology (UTAUT), is particularly valuable for studying the adoption of educational technology (ET) among educators. PE refers to the degree to which individuals believe that using a technology will enhance their job performance. In the context of educators, this translates to how effectively ET tools can improve teaching outcomes, streamline lesson delivery, and enhance student engagement and learning. If educators perceive ET as beneficial for achieving these goals, they are more likely to adopt and integrate such tools into their teaching practices. Therefore, highlighting the performance benefits of ET, such as improved efficiency and better educational outcomes, can positively influence educators' willingness to embrace technological innovations in education.

Since PE has shown to be the most robust predictor of BI, with statistical significance across all time points and models (Venkatesh et al., 2003; Prasad & Agarwal 1998; Venkatesh & Davis 2000; Higgins & Compeau 1995b; Taylor & Todd 1995a; Davis et al., 1992; Thompson et al., 1991), the same construct was adapted to the current study as well.

ii. Effort Expectancy (EE)

Effort Expectancy (EE) refers to how easy a technology is to use and apply, as highlighted by Venkatesh et al. (2003). Factors such as complexity, perceived difficulty, and ease of use from existing models (like TAM and TAM2) form the foundation of EE. Previous studies, including work by Davis et al. (1989), Plouffe et al. (2001), Moore & Benbasat (1991), and Thomson et al. (1991), indicate that these elements are closely related. Given these findings, EE becomes a relevant construct for understanding how educators adopt educational technology, as tools that are simpler and easier to use are more likely to be embraced in teaching environments.

From what we know so far, EE is highest in the outset. Longitudinal studies, however, have indicated that with continued usage, its significance declines (Agarwal & Prasad 1997; 1998; Thompson et al., 1991, 1994; Davis et al., 1989;). Early on in the process of adopting a new habit, when acceptance lethargy and initial adoption hurdles are most common, people are more likely to hold conceptions that center on the need to make an effort (Davis et al., 1989; Venkatesh 1999; Szajna 1996).

iii. Social Influence (SI)

Social influence plays a crucial role in understanding technology adoption, particularly when external expectations shape an individual's behavior. It refers to the pressure or encouragement an individual feels from people or groups they consider important, such as peers, supervisors, or influential figures, to adopt a particular technology. This concept is incorporated into several well-established theoretical models. For instance, in **TAM2** (Technology Acceptance Model 2), **TRA** (Theory of Reasoned Action), and **TPB/DTPB** (Theory of Planned

Behavior/Decomposed Theory of Planned Behavior), the *subjective norm* represents the perceived social pressure to perform a behavior. Similarly, in **MPCU** (Model of PC Utilization), social factors are emphasized, while in **C-TAM-TPB** (Combined TAM and TPB), social influence is also integrated. In the **IDT** (Innovation Diffusion Theory), the term *image* describes the perception that using a new technology enhances one's status within a group or organization.

Thompson et al. (1991) were among the first to highlight the similarities between social norms and the *subjective norm* from TRA, emphasizing that both concepts capture how individuals' decisions are influenced by others' expectations. Essentially, if educators believe that their peers, school leaders, or professional communities expect them to use a certain educational technology, this external influence can directly shape their behavioral intentions to adopt the technology.

However, it is important to note that while these social influence concepts are widely acknowledged and similar across models, their impact tends to vary based on the context. Venkatesh et al. (2013) argue that social influence is particularly relevant when individuals adopt a technology due to external pressures or organizational mandates. In contrast, its impact diminishes when individuals willingly accept and embrace technology based on their intrinsic motivation or perceived benefits.

In the context of **Education Technology (ET)** adoption among educators, social influence can be a significant factor, especially when educators are influenced by peers, institutional expectations, or professional development initiatives. For example, if a school administrator encourages the use of a new digital tool, or if other teachers begin to adopt a successful platform, educators may feel motivated to follow suit to meet expectations or align with institutional goals. Additionally, the perceived status or professional image associated with using cutting-edge technology can further drive adoption.

However, it is also crucial to recognize that educators who see clear value and benefits in using a particular technology may adopt it voluntarily, reducing the impact of social pressure. For instance, if educators find that a specific tool enhances student engagement, simplifies lesson planning, or improves learning outcomes, their decision to adopt the technology becomes less dependent on external influence and more rooted in personal conviction.

In summary, social influence provides a valuable lens to examine technology adoption, particularly when educators are influenced by social norms, professional expectations, or the desire to maintain their status within a peer group. However, its role may be limited when educators adopt educational technologies willingly, driven by perceived usefulness or performance gains. Therefore, understanding the balance between external pressures and intrinsic motivations is essential when studying the adoption of educational technology.

iv. Facilitating Conditions (FC)

An individual's view that an organization's environment or its pre-existing technological infrastructure and knowledge are conducive to the rollout of an invention is an example of a facilitating circumstance. Perceived behavioural control (C-TAM-TPB, TPB/DTPB), enabling conditions (MPCU), and compatibility are all condensed into one formulation. Each of these frameworks is created to make the technology and the surrounding business environment more user-friendly. Because of this conceptual similarity, Taylor & Todd (1995b) modelled facilitation as an essential element of perceived behavioural control in TPB/DTPB. In Innovation Diffusion Theory (IDT), the compatibility construct takes into account how well an individual's working style meshes with the business's intended use of the invention. In the educational context, facilitating conditions include access to:

- **Technical Infrastructure:** Reliable internet connectivity, functional hardware (laptops, tablets, projectors), and updated software are foundational for effective technology use (Bayaga & Du Plessis, 2024).

- **Training and Support:** Professional development workshops that train educators on using tools like Zoom or Google Meet increase their confidence and readiness to adopt new technologies (Abdullah et al., 2023).

- **Institutional Policies:** Supportive policies, such as reduced teaching loads to enable time for learning new tools, enhance adoption rates (Zaman, 2024).

Research suggests that the absence of such conditions creates significant barriers to technology integration (Chugh et al., 2023). For example, in rural or underfunded schools, inadequate internet bandwidth or outdated equipment often hampers educators' efforts to incorporate digital tools.

v. Perceived Enjoyment (PEj)/Hedonic Motivation (HM)

PEj also referred to as HM in some studies, refers to the degree to which an individual believes that utilizing ET is worthwhile; such persons also believe that such usage entails some level of delight (Wang et al., 2012). Additionally, it is shown that PEj has a large influence on technological innovation (Chong, 2013; Teo, 2006). While this notion enjoys widespread support, it remains a contentious factor, as several empirical investigations have discovered no correlation between reported enjoyment and technological adoption (Venkatesh et al., 2002). We believe that this construct will have a major impact on behavior intention due to the nature of ET and the segment that uses it.

vi. Behavior Intention (BI)

It is expected that BI will have a substantial positive impact on ET usage since it follows the same premise as all the other intention models discussed earlier. The TPB (Ajzen, 1991) evolved from Theory of Reasoned Action (TRA) to address the problem of partially voluntary action by adding the variable of perceived behavior control (PBC). Several studies on mobile education made use of TPB (Azizi & Khatony 2019; Raza et al. 2012; Cheon et al. 202l; Liu et al. 2010). McKnight et al. (1998) and McKnight et al. (2002) describe behavior intentions as the end user's "projection, anticipation, intention, and desire" to engage in or refrain from a certain activity.

Individuals' BI has a considerable impact on the amount to which and how far they are willing to go, as well as the work they are prepared to expend, to complete a task. As per TPB, an individual's attitude towards conduct describes the extent to which he or she has a positive or negative perception of the behavior.

Additionally, the push and pull elements associated with utilizing ET have a critical influence in defining the BI (Crompton, 1979; Uysal & Hagan, 1993). This notion attempts to describe how behavior is determined by the technology's push and pull factors. This may be compared to voluntary and involuntary usage, where volitional BI is generated during voluntary use of ET. Additionally, these aspects may include cognitive processes and socio-psychological reasons that influence people's decision to utilize a certain technology (Chon, 1989). The majority of push forces stem from humans' natural or latent needs, such as the desire for escape, novelty, adventure, dream fulfilment, proving one's self-worth, enjoyment, prestige, and self-fulfilment (Uysal & Jurowsky, 1993; Chon, 1989). Uysal & Hagan (1993) suggest that internal elements like self-efficacy or intrinsic motivation impact behavior intention to use a specific technology, while external ones like extrinsic motivation influence behavior intention to utilize a technology. Pull factors typically become active after the decision to use a certain technology is made, whereas push factors become active during the actual decision to use or not use a particular technology (Uysal & Hagan; 1993).

Several researches have been conducted to investigate the BI to use ET, with TAM serving as the cornerstone for all of these investigations. Phuangthong & Malisawan (2005) asserted that TAM was a useful model for assessing BI to adopt 3G technologies for education, whereas Jairak et.al., (2009) utilized the UTAUT developed by (Venkatesh et al. 2003) to assess BI to adopt m-learning technologies among university students.

vii. Use Behavior

The study wants to investigate the dimensions of ET use and will draw on the work of Blank and Groselj (2014) as a theoretical foundation. Blank and Groselj (2014) classify the dimensions of ET usage. Blank and Groselj (2014) drew their inspiration from Barton's (1955) concept of property space. They then created an internet-enabled property space utilizing Barton's (1955) approach. Then they find attributes that correspond to significant usage patterns. These qualities define dimensions that define an Internet-use space in which every individual can be situated according to their 'score' on each dimension. Blank and Groselj (2014) used these scores and an analysis of previous typologies to determine the main axes along which Internet usage varies. They proposed three aspects of internet usage: (1) amount, (2) variety, and (3) type.

The current study will use the same parameters to quantify ET usage.

In the study by **Blank and Groselj (2014)**, the authors focus on technology usage across different dimensions. These dimensions—**Amount of Technology Use**, **Variety of Technology Use**, and the extended **Variety of Technology Use**—can be effectively applied to the adoption of educational technology (ET) among educators.

Amount: The "amount" refers to how frequently educators use technology tools in their professional activities. This dimension measures the overall quantity or intensity of technology use within a specific period.

Example in ET Context:

A teacher using a learning management system (LMS) like Google Classroom daily to upload assignments, monitor student submissions, and provide feedback represents a high *amount* of technology use. Conversely, a teacher who uses the LMS once a week would show a lower *amount* of technology use.

Variety: "Variety" focuses on the range or diversity of technologies an educator uses in their teaching and administrative tasks. It reflects how many different types of tools or platforms are integrated into the educator's practice.

Example in ET Context:

An educator who uses various tools like Zoom for virtual classes, Kahoot for interactive quizzes, Microsoft Teams for collaboration, and Canva for designing teaching materials demonstrates a high variety of technology use. By contrast, a teacher who only uses PowerPoint for presentations would have a limited variety of technology use.

Type: This construct includes not only diverse tools but also the application of technologies across multiple contexts or activities, such as teaching, administrative tasks, and professional development.

Example in ET Context:

A teacher using Edmodo for student communication, Turnitin for checking assignments, and Padlet for brainstorming during lessons—while also using Excel for grading, LinkedIn Learning for professional development, and Trello for lesson planning—shows an extended type of technology use. The educator applies different tools across multiple aspects of their professional responsibilities, demonstrating comprehensive technology integration.

A comparable study was carried out by Liu et al. (2011) with the objectives of determining (1) whether the same beliefs (enjoyment, risk, and relative advantage) about using online channels that cause initial adoption also influence prolonged usage, (2) identifying the most influential factor(s) influencing every type of prolonged usage, and (3) investigating the effects of characteristics on prolonged usage of online channel among users. The study created a model to account for extended use of internet platforms. Three key criteria were found as driving continued usage: relative advantage, enjoyment, and risk. Three distinct modes of utilization were identified in this study: (1) online shopping, (2) information search, and (3) cross-channel purchase.

Shih et.al., (2017) used Shih & Venkatesh's use-diffusion (UD) model to analyze the post-adoption stage of VoIP telephony spread. This study stressed entirely on the post-adoption stage, hence broadening the research horizons for VoIP telephony diffusion. As predictors of use frequency and diversity, technological characteristics, personal dimensions, and external variables were discovered. In addition, they found that technical complexity, complementing technologies, human creativity, self-efficacy, a tendency to trust, media exposure, subjective norms, and word-of-mouth referrals were essential components of use diffusion. The rate of use can be increased by complementing technologies, self-efficacy, personal innovativeness, proclivity to trust, subjective norms, media exposure, and word-of-mouth (WOM) referrals. Variety of use can be increased by self-efficacy, proclivity to trust, media exposure, subjective norms, and word-of-mouth (WOM) referrals. Variety of use is essential for the prediction of UD results; when restricted use is used as the reference category, more than half of the UD determinants can correctly predict UD outcomes.

Zhu & Kraemer (2005) conducted a similar study in which they developed an integrative research model for analyzing the spread and consequences of e-commerce at the company level. Their primary concern was with the post-adoption stages, more precisely with actual usage and value development. They distinguished themselves from previous binary studies of "adoption vs non-adoption" by accounting for the "missing link" - actual usage - a critical stage of value growth. The concept provides a connection between technological, organizational, and environmental factors, as well as the use and value of electronic commerce. An application's worth is determined by its front-end functionality and backward integration. As a result, produced value impacts sales, internal operations, and procurement.

2.3.2 Moderators Used in the Study

2.3.2.A. Experience

Moderators although experience was not expressly mentioned in existing models, Davis et al. (1989) used a cross-sectional design to objectively explore the function of experience. Determinants' prominence remained unaffected. Yet, Karahanna et al. (1999) found that one's attitude becomes more significant while one's subjective norm becomes less so as one gains experience. The initial version of TAM did not take experience into account; nevertheless, research conducted by Szajna (1996) and Davis et al. (1989) among others, found actual evidence that Ease of Use (EU) becomes irrelevant with increased proficiency. The same is true of TPB and DTPB; none of them explicitly mentions experience in their studies. Experiential learning was subsequently included into TPB by Morris and Venkatesh (2000). These follow-up studies confirmed what Karahanna et al. (1999) had already shown concerning TRA, namely, that experience alters the relationship between subjective norm and BI such that subjective norm loses value as experience rises.

An individual's level of expertise was employed in C-TAM-TPB to categorize them as either seasoned pros or newbies. Subjective norm was less sensitive to experience compared to perceived benefit, attitude towards the conduct, and perceived behavioral control. Complexity, emotional investment in usage, social context, and supportive surroundings were shown to be more important to novices by Thomson et al. (1994). On the contrary, as experience rose, concern for long-term implications became more prominent. Karahanna et al. (1999) employed innovation diffusion theory (IDT) to perform a comparative investigation of the degree to which innovation was diffused across users with less/no experience and users with more experience. They came to the conclusion that the elements that influence adoption and usage are quite distinct from one another. According to the findings of the study, the most important factors in driving adoption were relative advantage and image, whereas the most important factors in driving use were relative advantage and simplicity of use. Trialability, demonstrability of results, and visibility were also found to be significant.

2.3.2.B. Gender

The first version of the TAM did not consider gender; however, subsequent versions based their suggestions on real research demonstrating that men put a larger value on perceived utility than on perceived ease of use. (Venkatesh & Morris 2000) Throughout the formative years of their lives, women gave greater weight to the importance of the subjective norm. At the beginning of their experiences, Venkatesh et al. (2000) discovered that men's attitudes were more important than women's subjective norms and perceived behavioural control. This was the case even though women's subjective norms and perceived behavioural control were more relevant. As the study found that the proportion of male and female educators is quite similar, Gender has been incorporated in the study and an important moderator. There is rich body of literature to support this.

The adoption of educational technology (ET) among educators is influenced by a variety of factors, including perceived usefulness, effort expectancy, social influence, and facilitating conditions. However, **gender** can significantly moderate the relationships between these factors and ET adoption. Previous research has consistently shown that men and women may respond differently to technology adoption due to differences in social roles, perceptions, and behavioral responses. Social role theory suggests that men and women often develop differing attitudes and behaviors due to socially constructed roles and expectations (Eagly & Wood, 2012). In ET adoption, this theory implies that gender may moderate the relationship between factors like ease of use and perceived usefulness. For example, women may prioritize user-friendly technology due to their tendency to focus on practical application and communal goals, whereas men may emphasize performance-driven outcomes (Hyde, 2014).

In academic contexts, Voyer & Voyer (2014) conducted a meta-analysis of gender differences in achievement and found that female educators often exhibit higher organizational adaptability and openness toward new tools when they perceive clear benefits. These differences can influence how educators engage with and adopt technology in the classroom.

Effort Expectancy (EE), which refers to the degree of ease associated with technology use, is a critical factor in ET adoption. Research shows that gender moderates coping strategies when individuals face technological or learning challenges. Tamres et. al., (2002) found that women tend to adopt more emotion-focused coping strategies, while men lean toward problem-solving approaches. In the context of ET adoption, these findings suggest that men and women may experience and respond to technological barriers differently, with women potentially requiring greater support systems and training to reduce perceived stress.

Gender differences in behavioral intentions toward technology adoption are also well-documented. For example, Ng & Feldman (2008) demonstrated that gender moderates job-related performance expectations, influencing attitudes toward technology in professional settings. In educational contexts, women may adopt technology more readily when they perceive its value for student-centered outcomes, while men may emphasize efficiency and productivity gains (Hyde, 2014; Vecchio, 2002).

Social Influence (SI), a core factor in adoption models like UTAUT, can also vary by gender. Studies suggest that women are often more influenced by peer relationships and societal norms when adopting new tools (Eagly & Wood, 2012). This aligns with findings by Helgeson (1994), who demonstrated that women are more likely to value communal connections and relationships, influencing their technology adoption decisions. Conversely, men may focus on task-related benefits, leading to different patterns of adoption in similar contexts.

Additionally, Chaplin et.al., (2008) highlight gender-specific responses to stress, which can influence how educators perceive and use technology under pressure. Women may feel more stress related to technological complexity, requiring user-friendly interfaces and clear instructional support.

Gender roles extend to leadership behaviors and organizational dynamics. Vecchio (2002) found that gender moderates perceptions of leadership effectiveness, which can influence how male and female educators implement technology. For example, female educators in leadership positions may focus on collaborative technology integration, while male educators may emphasize individual efficiency.

Based on the evidence, gender serves as a critical moderating factor in ET adoption. Differences in social roles, coping mechanisms, and behavioral intentions underscore the need for gender-sensitive approaches when designing and implementing ET. By acknowledging these gender-specific differences, policymakers and educational leaders can foster more inclusive and effective technology adoption strategies among educators.

2.3.2.C. Age

While attitude was shown to be more relevant for younger workers, Morris and Venkatesh (2000) discovered that perceived behavioural control was more significant for older workers. This was despite the fact that attitude was found to be more relevant for younger workers. It was shown that elderly women had an exceptionally high adherence to the subjective norm. In the academic setup, the blend of young and elder educators coexist, so it becomes quite pertinent to examine if age is a facilitator or an inhibitor of ET adoption.

Age has long been recognized as a significant factor that influences technology adoption, with different age groups often demonstrating varying levels of familiarity, comfort, and enthusiasm for new tools. In the context of educational technology (ET) adoption among educators, age can serve as a **moderator** that impacts how key determinants such as perceived usefulness, effort expectancy, and social influence affect behavioral intentions.

Research has shown that older individuals may perceive new technologies as less useful due to limited exposure and their established teaching practices (Morris & Venkatesh, 2000). Older educators, for instance, may be hesitant to adopt educational technologies if they do not clearly perceive their benefits for instructional improvement. In contrast, younger educators, who often belong to technology-savvy generations, tend to view ET as essential tools that enhance teaching efficiency and engagement (Venkatesh et al., 2012).

For example, Czaja et al. (2006) found that older adults are more likely to question the usefulness of technologies that require substantial adjustments to their existing practices. In education, older teachers might perceive a higher cost-benefit trade-off when adopting technologies like interactive whiteboards, while younger teachers might embrace them quickly as they are accustomed to digital tools.

Effort Expectancy (EE), which refers to the perceived ease of using technology, is strongly moderated by age. Older educators often face challenges such as lower digital literacy and difficulty adapting to technological advancements, leading to higher perceptions of effort (Morris et al. 2005). Conversely, younger educators, who have grown up with digital devices, often find it easier to learn and adopt new technologies.

For instance, research by Charness & Boot (2009) highlights that cognitive aging can affect the ability to learn new interfaces and adapt to complex tools. In the educational setting, this means older teachers may require more training and support when adopting learning management systems, digital gradebooks, or online teaching platforms, while younger educators may navigate them with minimal effort.

Social Influence (SI), such as peer pressure and institutional expectations, can also be moderated by age. Venkatesh et al. (2003) demonstrated that older individuals are more likely to be influenced by colleagues or authority figures when deciding whether to adopt technology, while younger individuals tend to rely on personal experiences or peer groups for validation.

In educational contexts, older teachers may respond more strongly to encouragement from institutional leadership or professional development workshops. For example, if institutional administrators promote the use of ET, older educators may adopt these tools to align with institutional norms. On the other hand, younger educators may be influenced by peer recommendations or trends among fellow teachers on social platforms.

Behavioral Intention (BI) to adopt technology tends to decline with age, primarily due to reduced self-efficacy and increased resistance to change (Morris et al., 2005). Studies show that older educators may feel less confident in their ability to integrate technology into their teaching practices effectively. Self-efficacy, which refers to one’s belief in their ability to use technology successfully, often diminishes with age unless proper training and support are provided (Bandura, 1997; Venkatesh et al., 2012).

For example, teachers over 50 may prefer traditional teaching methods and may only adopt ET when necessary, such as during the COVID-19 pandemic when online learning became unavoidable. Younger educators, on the other hand, often show higher behavioral intentions to adopt ET as they are more confident in exploring and utilizing digital tools (Teo, 2011).

The relationship between facilitating conditions (FC) (e.g., support and training) and technology adoption is also moderated by age. Older educators typically require more structured training and ongoing technical support to overcome perceived barriers to technology adoption (Czaja et al., 2006). Younger educators, however, may benefit more from flexible, self-directed training modules that cater to their existing technological proficiency (Venkatesh et al., 2003).

Age plays a significant moderating role in the adoption of educational technology among educators. Older educators may perceive greater challenges related to effort expectancy, perceived usefulness, and behavioral intentions, while younger educators tend to adopt technology more readily due to higher digital literacy and confidence. Recognizing these age-related differences can help policymakers and administrators design targeted interventions, such as age-specific training programs, to ensure inclusive and effective technology adoption across all age groups.

2.3.2.D. University Type

Through several discussions with educators and CEO's of EdTech companies, it was always harped upon that Central Universities are resource rich whereas the State and Private Universities are resource-strapped. This enables the Central Universities to acquire advanced and latest technologies and also become the hubs of innovation and research. This introduced an interesting facet to the study and this study tried to test if the University Type influenced the ET adoption. So this construct was inducted as a moderator in the study. There is also rich literature background to support this decision.

The type of university—whether state or central—can significantly influence educators' adoption of educational technology (ET). This moderating effect stems from differences in institutional funding, infrastructure, administrative support, and organizational culture. State universities and central universities often operate under distinct resource conditions, which can impact educators' perceptions, readiness, and behavioral intentions to adopt new technologies.

One of the key factors that differentiate state universities from central universities is the availability of financial resources and infrastructure. Central universities, often funded and managed directly by the central government, tend to have better infrastructure, more advanced technological facilities, and access to robust funding for implementing ET (Prasad & Mishra, 2018). In contrast, state universities may face resource constraints due to limited state-level budgets, which can hinder technology integration.

For instance, educators in central universities may have access to high-speed internet, advanced learning management systems (LMS), and modern tools like smart classrooms, making it easier to adopt educational technologies. On the other hand, educators in state universities may struggle with outdated systems, unreliable internet connectivity, and insufficient IT support, which can slow down the adoption process (Alam & Khalifa, 2019).

The level of institutional support often varies between central and state universities, influencing the adoption of ET. Central universities, with their relatively larger administrative budgets and national reach, are more likely to offer structured professional development programs, technical support, and incentives to educators for integrating technology into their teaching practices (Jhurree, 2005). This supportive environment can positively influence educators' behavioral intentions and perceived ease of using educational technology.

Conversely, state universities may face bureaucratic delays or limited administrative prioritization when implementing ET initiatives. Educators in these universities might perceive the adoption of new technologies as a burden if adequate training and support systems are lacking. For example, researchers have shown that insufficient technical assistance and training programs act as major barriers for educators in resource-limited institutions (Mumtaz, 2000).

University type often influences organizational culture and policy direction, which can act as a moderating factor. Central universities may be more proactive in adopting national-level educational technology policies and initiatives due to their direct alignment with central government agendas. For instance, central universities might more readily implement platforms like MOOCs (Massive Open Online Courses) or digital initiatives like SWAYAM, an e-learning platform launched by the Indian government (Mishra, 2017). Educators in these universities may feel greater institutional pressure to adopt and utilize ET tools effectively.

In contrast, state universities often operate under state-specific educational policies and may adopt ET at a slower pace. Educators in such environments might face less organizational push to adopt new technologies, leading to lower levels of motivation or urgency to integrate ET into their practices (Tarhini et al., 2015).

Central universities are generally better positioned to provide faculty development programs aimed at enhancing digital literacy and technological competency among educators. Studies have shown that access to regular training workshops and capacity-building initiatives significantly influences educators' attitudes toward technology adoption (Teo, 2011). In contrast, educators in state universities may receive limited training opportunities due to financial and organizational constraints. This disparity can widen the gap in ET adoption between central and state university educators.

For instance, a study by Sahin & Thompson (2007) highlights the importance of professional development in overcoming educators' resistance to technology. Educators in central universities, equipped with more structured training, are likely to feel more confident and competent in using ET tools compared to their state university counterparts.

Differences in university type can also moderate educators' perceptions of the usefulness and effort required to adopt ET. In central universities, where technological infrastructure and support systems are robust, educators may perceive ET as more useful and easier to implement in their teaching processes (Venkatesh et al., 2003). For example, digital tools like virtual labs and e-learning platforms are seen as highly beneficial when supported by appropriate infrastructure.

In contrast, educators in state universities may perceive higher levels of effort expectancy, as they often face challenges like unreliable technology, lack of IT support, and unfamiliarity with advanced tools (Zhao & Frank, 2003). These challenges can lead to lower perceptions of usefulness and greater resistance to ET adoption.

University type serves as a significant moderator in the adoption of ET among educators. Educators in central universities benefit from superior infrastructure, institutional support, and access to training, which positively influence their technology adoption. In contrast, state university educators often face challenges related to resource constraints, limited support, and organizational barriers, which can impede ET adoption. Recognizing these differences can help policymakers and institutional leaders design targeted interventions to bridge the technology adoption gap across different university types.

2.4 Proposed Research Model

The proposed research model is depicted in Figure 2.1.

2.4.1. Operational Definitions of the Constructs

Performance Expectancy (PE)

Performance Expectancy refers to the degree to which an individual believes that using a specific technology will improve their job performance or productivity. In the context of education technology adoption among educators, PE can be operationalized as the extent to which educators perceive that using educational technologies (e.g., LMS, virtual classrooms, or digital tools) enhances teaching effectiveness, student engagement, and overall instructional quality.

***Example*:** "Using an online learning management system improves my ability to organize course content efficiently."

Effort Expectancy (EE)

Effort Expectancy is defined as the degree of ease associated with the use of a particular technology. It focuses on the user's perception of how simple or intuitive the technology is to operate. For educators, this includes the clarity of the interface, ease of navigation, and the learning curve for adopting new educational tools.

Example: "Using a digital assessment tool is easy to learn and requires minimal effort to operate."

Social Influence (SI)

Social Influence refers to the extent to which individuals perceive that important people, such as colleagues, administrators, or peers, believe they should use the technology. It also includes institutional norms and peer pressure in an educational setting.

Example**:** "My colleagues and administrators encourage me to use online teaching platforms to improve course delivery."

Perceived Enjoyment (PEj)/Hedonic Motivation (HM)

Perceived Enjoyment (PEj) or Hedonic Motivation (HM) refers to the fun, pleasure, or intrinsic satisfaction derived from using a particular technology. In the context of ET adoption, it can be seen as the enjoyment educators experience while exploring creative or interactive teaching methods enabled by technology.

Example**:** "I find using interactive tools like virtual whiteboards enjoyable and satisfying during my teaching sessions."

Facilitating Conditions (FC)

Facilitating Conditions are defined as the perceived availability of resources, infrastructure, and support that make it easier to use a technology. For educators, this includes technical support, availability of devices, training programs, and reliable internet connectivity.

Example**:** "My institution provides sufficient resources, such as reliable internet and technical support, to help me adopt educational technologies."

Behavior Intention (BI)

Behavior Intention refers to an individual’s intention or willingness to use a specific technology in the future. In the educational technology context, BI indicates how likely educators are to use digital tools for their teaching or administrative tasks.

Example**:** "I intend to use digital platforms for lesson planning and student assessments regularly."

Actual Use (AU)

Actual Use is the extent to which an individual actually uses a specific technology in their daily work. It reflects the observable and measurable usage of ET by educators in their teaching practices.

***Example*:** "I use video conferencing tools like Zoom or Google Meet in at least 80% of my lectures."

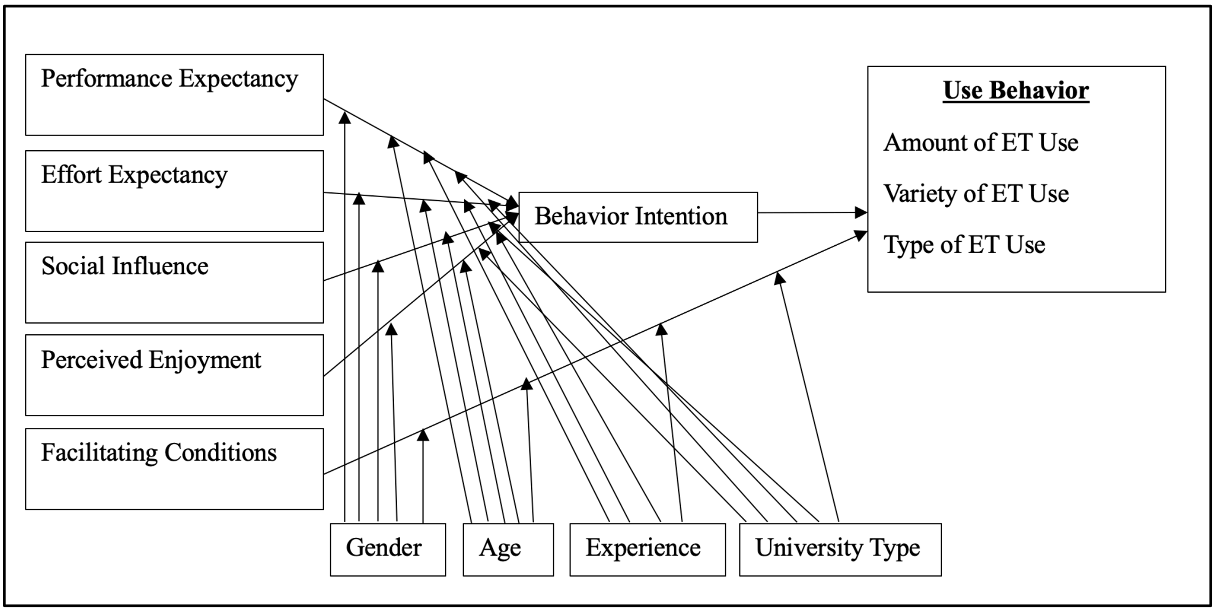

Fig 2.1: Research Framework of the Study

Source: Developed by the Author

The following present the state of the art status of the extant literature available on UTAUT and ET.

2.5 Bibliometric Analysis of Literature on Education Technology.

Related research papers from the SCOPUS database were analyzed using a hybrid bibliometric technique to understand how it has evolved from the perspective of academic communities. Cluster Analysis together with direct citation network technique, was used to demonstrate how the field of ET research has evolved over the course of time in higher education. This was done in addition to the use of visual analytics to examine ET research. There were five main ways that ET was being enhanced, which were shown by the articles regarding ET development that were referred internally the most often. These strategies were adoption, criticism, social media, podcasting, and blended learning. After that, the information that had been gathered was put together with the use of latent semantic analysis in order to reveal the most critical subgroup concerns in each stream. The hybrid strategy that has been suggested is a technique to get a comprehensive assimilation of the evolution of research in the realms of ET in higher education more rapidly. It encompasses the primary research strands, pertinent subgroup issues, and a comprehensive listing of essential papers.

Only works that had been published in academic journals that had been peer-reviewed were considered for review. This was done to ensure that the publications were of a high quality. This meant that book publications and conference proceedings were not taken into consideration. To conduct this research on the research environment, articles from the Scopus database that were published between 2006 and December 2021 were utilized. The articles came from Elsevier's Scopus Collection, that contains the most comprehensive collection of bibliographic and citation data for publications in the fields of humanities, social sciences, and natural sciences. These records were used to compile the articles.

The search parameters for ET associated with the research need to be established so that UTAUT and ET-related literature may be located. Thus, we created a category that we term "ET-related papers" and placed those publications in higher education that had the phrases technology, learning, and teaching in their titles, abstracts, or keywords in those papers. Hence, on the Scopus page for advanced searches, the search terms (technolog) AND (learn* OR teach*) AND ('higher educat* OR universit*) were used. The * is what's known as a "wildcard" character since it may be used for almost any other letter or number. By using these criteria, a total of 1,603 publications discussing the ways in which technology is used in higher education were located. The research does not claim to have generated a comprehensive list since the data retrieval step only looked at the titles, abstracts, and keywords of publications and did not look at the substance of the articles themselves. Nevertheless, a large chunk of publications were read to gain a sense of the scientific environment around ET.

2.5.1. Data Acquisition

Bibliographic data can be retrieved by querying the SCOPUS database using a variety of fields, including topic, author, journal, and time period.

We demonstrate how the data was downloaded in this segment by querying a few keywords in the manuscript title field.

2.5.1.A. “bibliometrix” Installation

Firstly, the most recent version of R was downloaded and installed from (https://cran.r-project.org). Then the latest version of R Studio was downloaded and installed from (https://rstudio.com). Then the R Studio is opened, and the following script was used to install the bibliometrix package along with its dependencies.

```
install.packages(“bibliometrix”, dependencies=TRUE) ### installs bibliometrix package and dependencies.
install.packages(“bibliometrix”, dependencies=TRUE) ### installs bibliometrix package and dependencies.
library(bibliometrix)    ### load bibliometrix package
```

2.5.1.B. Data Loading and Converting

The export file can be read and converted using by R using the function *convert2df*:

convert2df(*file*, *dbsource*, *format*)

```
scopus <- convert2df(file = file, dbsource = "isi", format = "bibtex")
```

The convert2df programme generates a bibliographic data frame with cases that correspond to articles and variables that correspond to Field Tag in the original export file.

convert2df accepts two additional arguments: *dbsource* and *format*.

The value of the dbsource parameter may be used to determine which database the collection was obtained from.

It can be:

- “scopus” (for SCOPUS database),
- “isi” or “wos” (for Clarivate Analytics Web of Science database),
- “pubmed” (for PubMed/Medline database),
- “dimensions” (for DS Dimensions database)
- “cochrane” (for Cochrane Library database of systematic reviews).

The file format of the imported collection may be determined by looking at the parameter format. For the WOS collection, "plaintext" or "bibtex" are both acceptable formats, however for the SCOPUS collection, "bibtext" is required. If the collection was obtained from Pubmed or Cochrane, the argument is not taken into consideration.

Every single document has various components, such as the names of the writers, the title, a list of keywords, and other information. The bibliographic properties of a document are comprised of all of these components, which are also referred to as metadata.

2.6. Visual Representation of Bibliometric Data

2.6.1. Most Relevant Sources

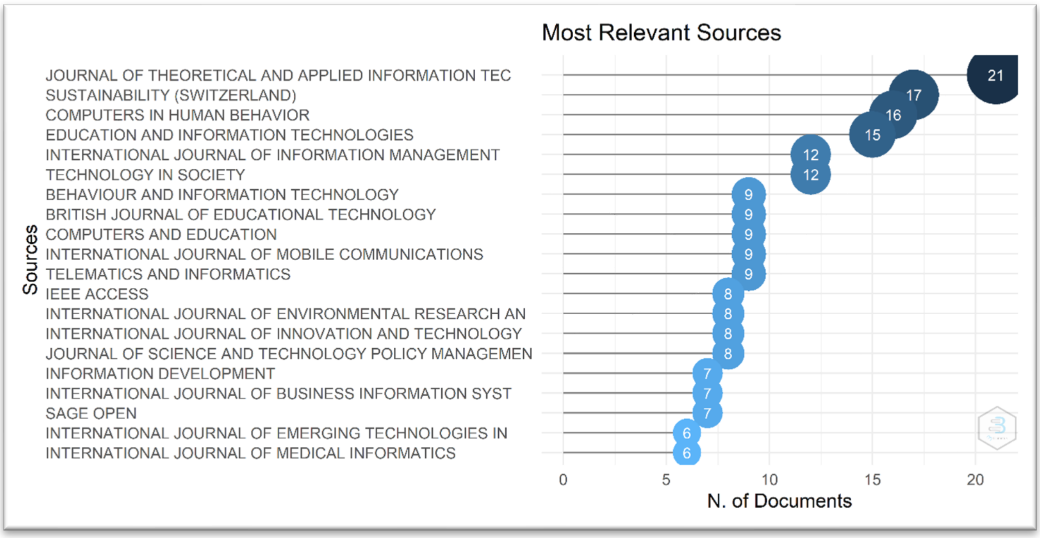

Fig 2.2: Most Relevant Sources

The above visualization is related to a bibliometric analysis to definitively determine the most relevant sources. Bibliometric analysis focuses on analyzing scholarly publications using statistical methods. Here's what the different elements in the visualization indicate:

- **Most Relevant Sources:** This section refers to the academic journals that are most relevant to the research topic being investigated in the bibliometric analysis. To 20 journals are presented in the visual which have been used in the current study.
- **Journal Titles:** Titles of academic journals are listed here. These are the journals that published the most relevant articles or the journals that were cited the most often in the articles included in the analysis.
- **Document Counts:** Numbers here indicate the number of articles published in each journal included in the analysis.

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2.6.2. Source Local Impact by Total Citation (TC) Index

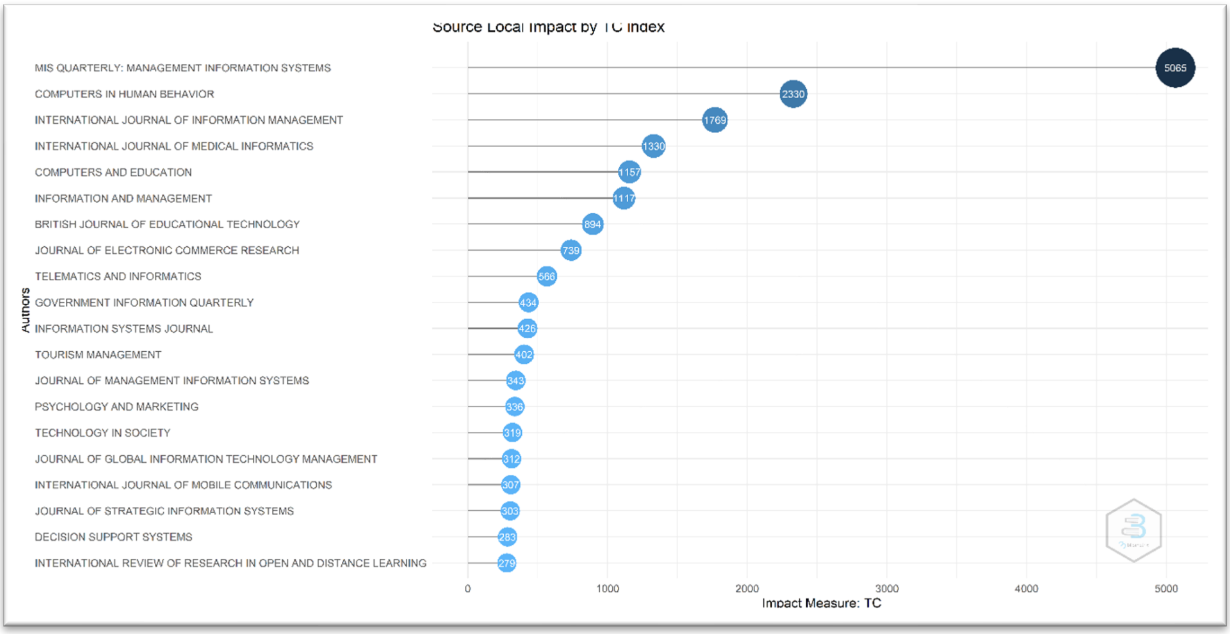

Fig 2.3: Source Local Impact by Total Citation (TC) Index

The visualization presented in the image is a lollipop chart showing the Source Local Impact by Total Citation (TC) Index for various academic journals. The Total Citation (TC) Index is a simple metric that counts the total number of citations received by a source (journal) in a specific period.

Here's a breakdown of the image:

- **X-axis:** The x-axis represents the total number of citations (TC Index) for each source. Higher TC Index values indicate a greater number of citations and potentially higher local impact on the field of research.
- **Y-axis:** The y-axis lists the titles of the academic journals included in the analysis.

For instance, the journal "MIS QUARTERLY" appears to have the highest TC Index (5366), followed by "COMPUTERS IN HUMAN BEHAVIOR" (2300). This suggests that these journals have received the most citations within the specified time frame, compared to the other journals in the analysis.

2.6.3. Most Relevant Authors by Number of Publications

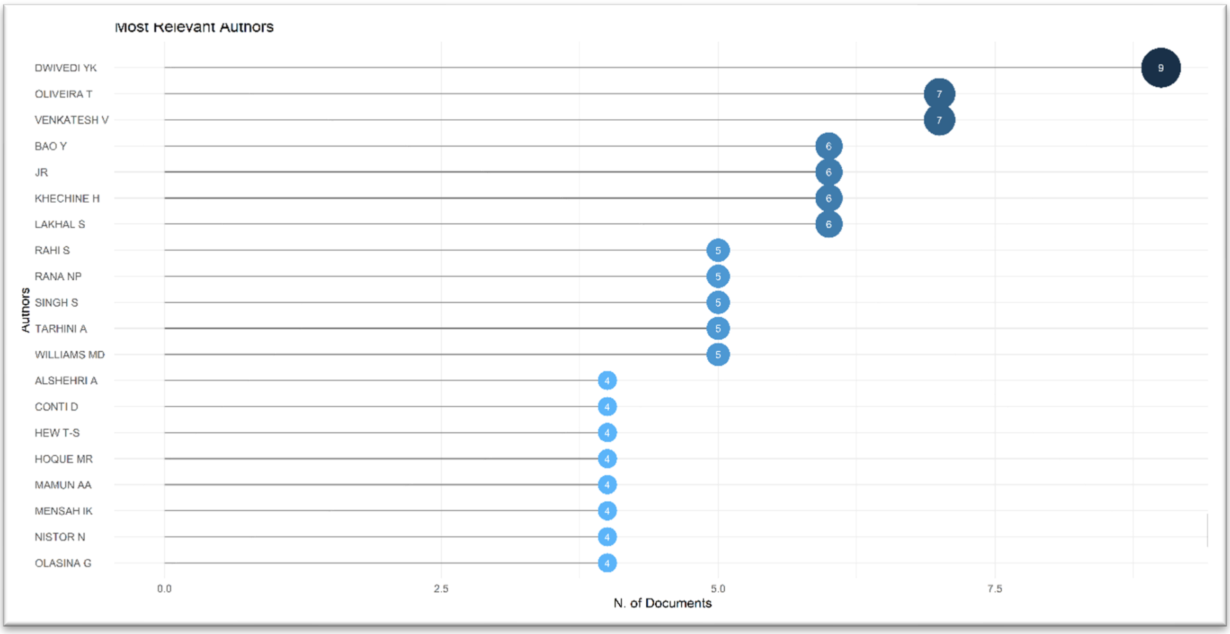

Fig 2.4: Most Relevant Authors by Number of Publications

The visualization presented above shows the most relevant authors by number of publications in the said field of research. The most relevant authors are those who have published the most articles in that field.

- **X-axis:** The x-axis represents the number of publications by each author.
- **Y-axis:** The y-axis likely represents the number of publications by each author. The scale may not be linear, so the differences between bars may not represent equal differences in publication counts.

For instance, in the image you sent, the author "DWIVEDI YK" appears to have the most publications (9), followed by "CLIVEIRAT PL" and "VENKATESH V" (both with 7 publications).

2.6.4. Most Relevant Affiliations

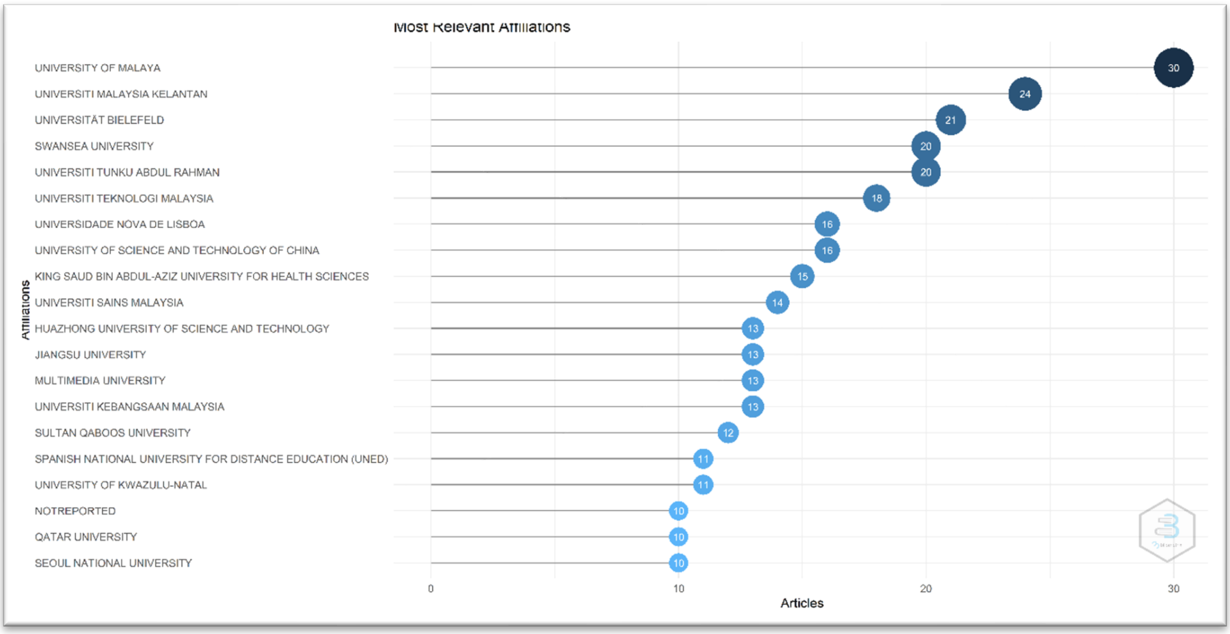

Fig 2.5: Most Relevant Affiliations

The visualization presented in the image shows the most relevant affiliations for articles included in a bibliometric analysis, based on the number of publications affiliated with each institution.

- **X-axis:** Number of articles affiliated with each institution.
- **Y-axis:** lists the names of various universities or research institutions.

For instance, in the image "UNIVERSITY OF MALAYA" appears to have the most articles (30), followed by " UNIVERSITI MALAYSIA KELANTAN" with 24 articles.

Interpretation

This visualization indicates the universities or research institutions that have published the most articles relevant to the field of study explored in the bibliometric analysis. It suggests a higher publication activity from these particular affiliations.

2.6.5. Most Prolific Countries

Table 2.1: Most Prolific Countries

Country	Contribution
Malaysia	373
USA	308
China	302
India	161
UK	126
Indonesia	102
Australia	83
Saudi Arabia	80
Germany	79
South Korea	73
Spain	73
South Africa	70
Bangladesh	56
Jordan	50
Thailand	50
Canada	49
Iran	46
Pakistan	45
Ghana	43
Portugal	38

2.6.6. Most Cited Countries

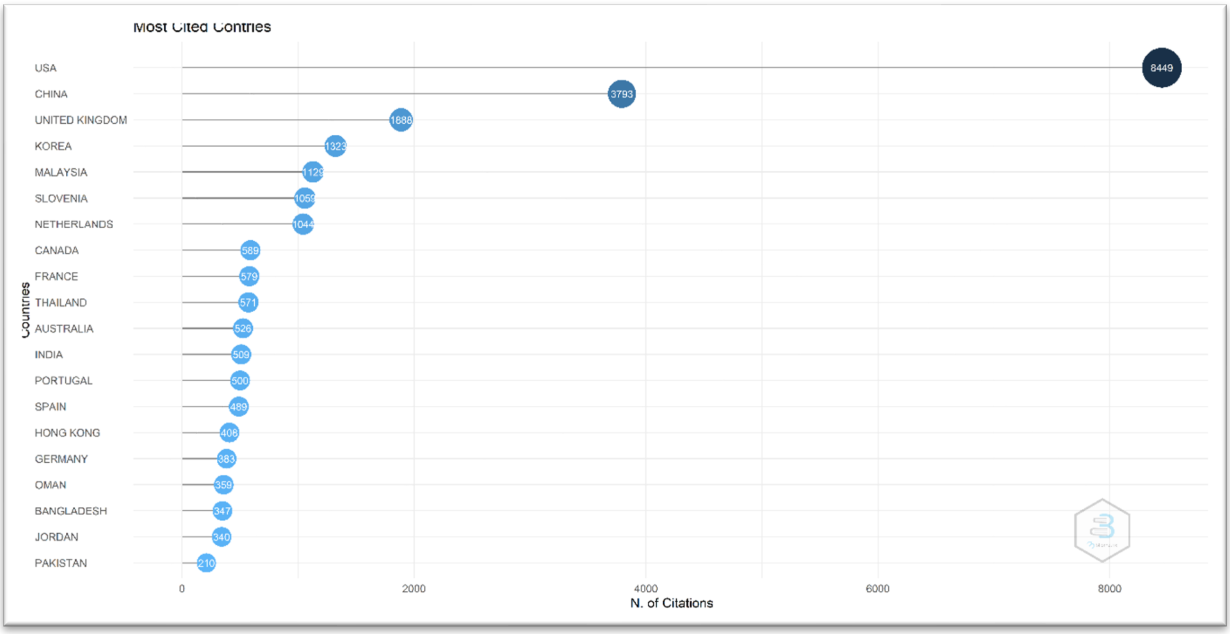

Fig 2.6: Most Cited Countries

The visualization presented in the image shows the most cited countries in the research study, based on the number of citations received by articles from each country.

- **X-axis:** shows the number of citations received by articles from each country (N. of Citations).

- **Y-axis**: lists the names of various countries.

For instance, in the visual, the United States (USA) appears to be the most cited country (with 8449 citations), followed by China (with 3793 citations) and the United Kingdom (UK) with 1888 citations.

Interpretation

This visualization indicates the countries that have had the most impact on the field of study in the bibliometric analysis, based on the citation counts of articles from those countries. Countries with higher citation counts suggest that researchers have found a lot of value in the work produced by those countries.

2.6.7. Trend of Topics Over Time Based on Author's Keywords

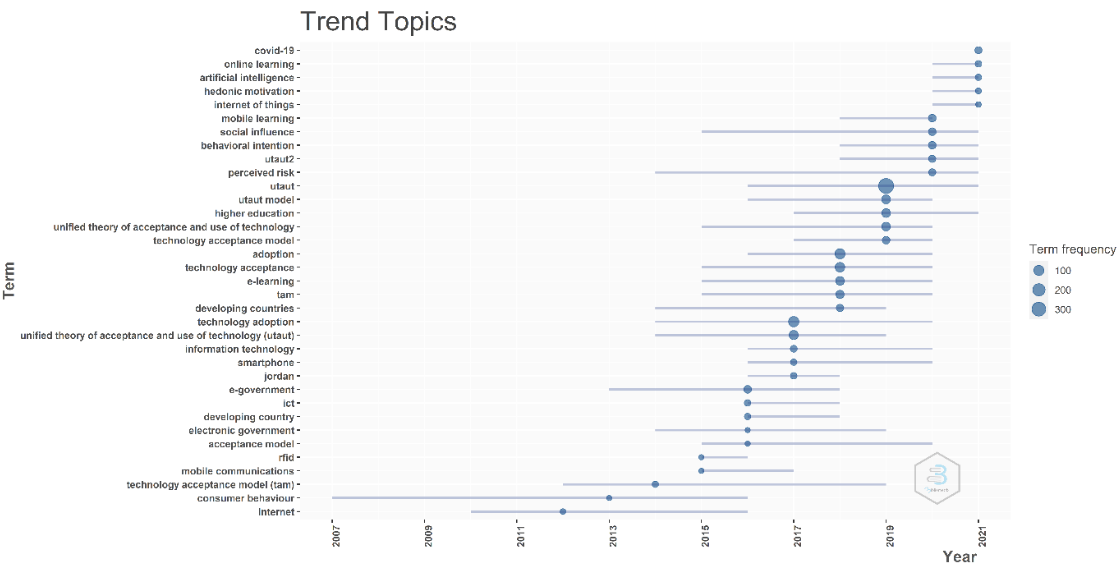

Fig 2.7: Trend of Topics Over Time Based on Author's Keywords

The visualization presented in the image shows the trend of topics over time based on author's keywords. The x-axis represents the year of publication, and the y-axis represents the document frequency, likely the number of documents (articles) published that mention that specific keyword. The size of the circle corresponds to the document frequency. Here are some additional observations based on the image:

- **Early Years (2007-2010):** The dominant topics in this period seem to be "technology acceptance model (TAM)", "information technology (IT)", "e-learning", and "adoption." This suggests a focus on understanding how people adopt and use new technologies in an educational context.

- **Later Years (2011-2017):** There seems to be a shift in focus towards mobile learning ("mobile learning", "m-learning") and social influence ("social influence") on technology adoption. This suggests a growing interest in the role of mobile technologies and social factors in shaping technology use in education.
- **Emerging Trends:** Keywords like "internet of things (IoT)", "perceived risk", "behavioral intention", and "hedonic motivation" appear in the later years (2013-2017). This suggests a possible emerging interest in understanding the role of IoT in education, the factors influencing learners' risk perceptions and behavioral intentions towards technology use, and the role of enjoyment or intrinsic motivation in technology adoption.

Overall, the visualization provides a snapshot of how research focus has evolved in this field based on the keywords used by authors. It suggests a shift from a focus on traditional technology acceptance models to a broader interest in mobile learning, social influence, and emerging technologies like IoT in the context of ET adoption

2.6.8. Clusters by Document Coupling - MAP

Coupling Map Parameters

Units of Analysis: Documents

Coupling Measured by: Author’s Keywords

Impact Measure: Global Citation Score

Cluster Labeling by: Author’s Keywords

Number of Units: 250

Minimum Cluster Frequency: 5%

Labels per Cluster: 3

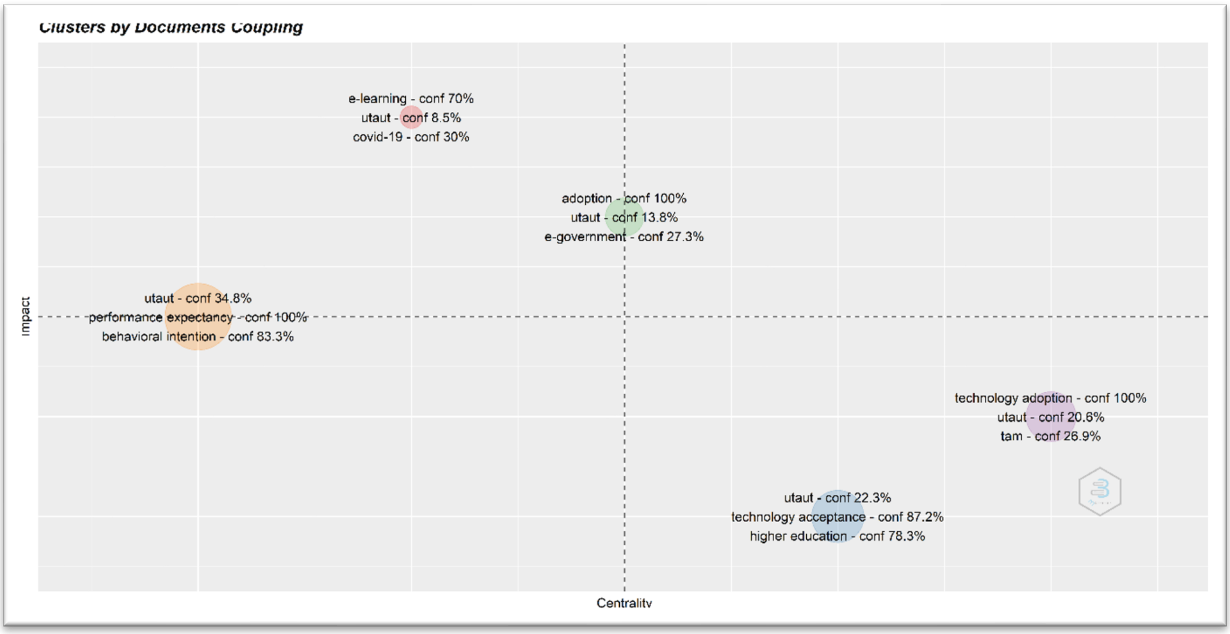

Fig 2.8: Clusters by Document Coupling - MAP

The visualization is a cluster diagram generated from a bibliometric analysis. It depicts the centroid based clustering of data points or documents. In this case, the documents are research articles related to a specific field, and the clustering is based on document coupling.

Document Coupling

Document coupling refers to the number of citations or references shared between two documents. Documents that share a lot of references are considered to be more closely coupled because they likely cover similar topics or research areas.

Interpretation

- The x-axis represents the distance between clusters. Documents within a cluster are more similar to each other than documents in different clusters based on the document coupling metric.
- The vertical lines in the dendrogram represent documents or clusters of documents.
- The horizontal lines represent the merging of clusters. The height of the horizontal line indicates the distance or level of similarity between the documents or clusters that were merged at that point.

2.6.9. Factorial Analysis – Word Map

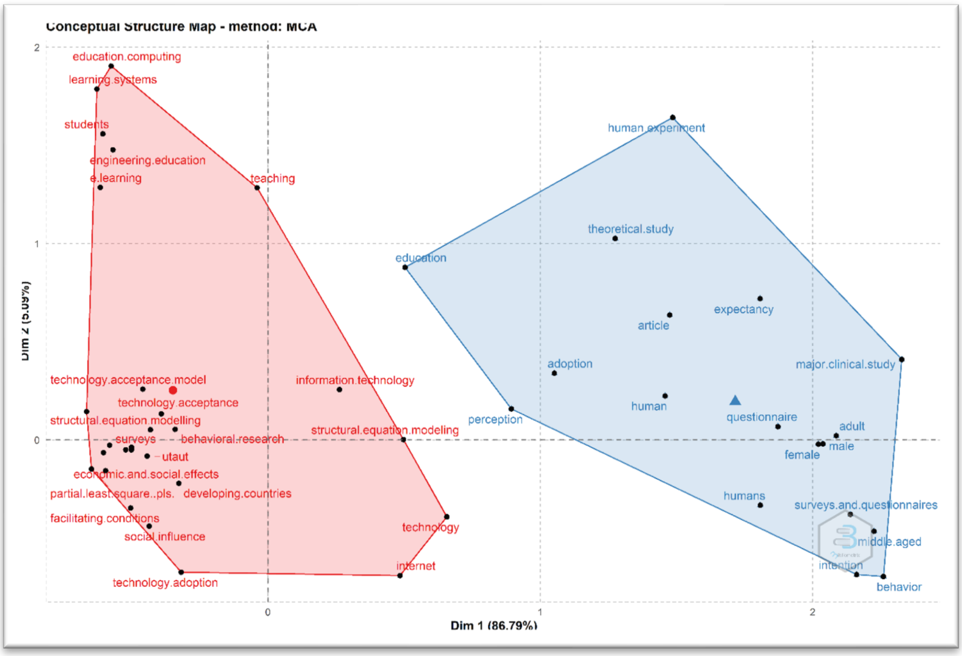

Fig 2.9: Factorial Analysis – Word Map

The visualization is a conceptual structure map created using Multiple Correspondence Analysis (MCA), a type of factorial analysis. This method is used to explore relationships between categorical variables by representing them in a two-dimensional space. In this case, the categories are the keywords used in a set of bibliographic documents.

Here's a breakdown of the information presented in the image:

- **Dimensions:** The map uses two dimensions, Dim 1 (horizontal axis) and Dim 2 (vertical axis), to represent the relationships between the keywords. Each axis explains a certain percentage of the total variance in the data (shown as percentages in brackets next to the axis labels). In the image you sent, Dim 1 accounts for 86.79% of the variance and Dim 2 accounts for 5.09%.
- **Keywords:** The circles in the map represent the different keywords identified in the bibliographic documents. The size of the circle might indicate the frequency of the keyword (larger circles likely represent more frequent keywords).
- **Positioning:** The position of a keyword within the map reflects its relationship to other keywords. Keywords that co-occur frequently in the documents tend to be positioned closer together in the map. The distance between keywords suggests the strength of their association.

Interpretation

There appear to be four clusters of keywords based on their proximity in the map.

- **Cluster 1 (upper left):** This cluster includes keywords like "education.computing," "learning.systems," "students," and "engineering.education." These terms seem to be related to the field of educational technology or learning systems used in education.
- **Cluster 2 (lower left):** This cluster includes keywords like "structural equation modeling," "technology acceptance model," "information technology," and "perception." These terms appear to be related to research methods or theoretical frameworks used in technology acceptance research.
- **Cluster 3 (right side):** This cluster includes keywords like "perceptual ease," "facilitating conditions," "social influence," and "technology adoption." These terms are likely related to factors influencing technology adoption behavior.
- **Cluster 4 (upper right):** This cluster is a bit separated from the others. The only keyword visible is "article." It's possible that this cluster includes keywords related to the types of documents included in the analysis (e.g., research articles, surveys).

Overall, the conceptual structure map provides a visual representation of how keywords are interrelated within a set of bibliographic documents. It can be a useful tool for identifying thematic areas and relationships between concepts in a research field.

2.7. Research Gap

Quality education contributes to the development of a nation's human capital. To avoid squandering its demographic dividend, India's education system must undergo significant reforms. In this context, it is critical to evaluate the levels of acceptance of technology in the field of education from the point of view of the two primary stakeholders, namely students and educators. According to a NASSCOM report on the Indian Start-Up Ecosystem (2017), the top two sectors in which start-ups addressing social problems are mushrooming in India are Healthcare and Education Inclusion. Numerous ET start-ups have sprung up to address issues such as distance education, education loans, scholarship crowdfunding platforms, and education and training platforms.

The problem is significant in scope. The extant body of knowledge in the ET domain is fragmented. The available literature is highly specialized, focusing on Digital or Hybrid Libraries, MOOCs, or Digital Classrooms. That is, studies have concentrated their efforts on a single product or service. The acceptance, adoption, and dissemination of ET on a broad scale have rarely been addressed.

From this exhaustive analysis, we could see that there hasn't been much emphasis on ET. There have been a few studies on E-Learning, but ET is a much broader term, which needs special attention.

This review of the relevant literature demonstrates that ET has been overlooked despite the fact that it belongs to one of the most developed fields of study. A plethora of fresh research possibilities has arisen and is continuing to develop because of the recent broad adoption and usage of customer-facing technology in the area of education (Williams, 2015).

An exhaustive review of existing literature reveals the following glaring gaps:

1. In the same way that the introduction of the World Wide Web in 1993 necessitated the emergence of new theoretical and conceptual frameworks for the study of customer experience (Novak & Hoffman 1996), we think that ET could benefit from a conceptual framework that describes how customer experience and ET experience emerge from the myriad of interactions that take place between educators and devices. (Hoffman and Novak, 2016)
2. Numerous studies have looked at what elements influence people's willingness to try new technologies and how successful they end up being. Despite this, there have been little efforts to delve into ET, especially with regards to post-adoption research that focuses on how users feel about and how heavily they use information systems (Saeed & Abdinnour-Helm, 2008).
3. While previous studies in the field of ET focus on environments of voluntary adoption, studies on ET in mandatory use context is scanty (Brown et al., 2002).
4. Similar studies in the past have used purposive sampling in limited settings and that too on a single Learning Management Tool (LMS) (Fathema et al., 2015).
5. The organization type also has a vital bearing on the diffusion of technology within the organization. The facilitating conditions could vary drastically within various types of educational institutions such as Central Universities and State Universities.

In conclusion, this literature review has meticulously examined the various theories, models, and empirical studies pertinent to the adoption and use of educational technology (ET) in higher education. The Unified Theory of Acceptance and Use of Technology (UTAUT) and its extended models have provided a robust framework to understand the factors influencing ET adoption, including performance expectancy, effort expectancy, social influence, facilitating conditions, and perceived enjoyment. The bibliometric analysis further highlighted the prominent sources, influential authors, and emerging research trends in the field, underscoring the dynamic and evolving nature of ET research.

The comprehensive review identified significant gaps in the current literature, particularly the need for a holistic understanding of ET adoption beyond isolated technologies and single-use cases. The incorporation of demographic moderators such as age, gender, experience, and university type adds a nuanced perspective to the understanding of ET adoption in diverse educational contexts. Additionally, the review emphasizes the importance of examining post-adoption behavior and the role of consumer experience in the sustained use of ET.

The insights gained from this review will guide the methodological approach and analysis in the following chapters, contributing to a more comprehensive and informed understanding of ET adoption and its implications for higher education in India. This scholarly endeavor aims to bridge the existing gaps and provide actionable insights for educators, policymakers, and technology developers, fostering a more effective and inclusive integration of technology in education.

2.8 Proposed Contributions of the Framework

This adapted UTAUT framework is particularly relevant in the Indian educational context, where digital transformation in teaching is gaining momentum. The model provides a structured approach to analyze factors influencing educators' adoption of ET tools. By incorporating **perceived enjoyment** and moderating variables like **university type**, the framework addresses both intrinsic and extrinsic factors unique to the Indian higher education system.

CHAPTER-3

RESEARCH METHODOLOGY

3.1 Introduction

This chapter discusses the study's research methodologies. It discusses the objectives of the study, conceptualized research model, hypothesis, research design, variables with operational definitions, research type, methods, sampling technique, sampling population, sampling size, and sampling procedure, questionnaire design and development, , content validity, pilot survey, and execution of the survey.

3.2 Objectives of the Study

Following objectives have been considered for the study.

1. To investigate the relationship between performance expectancy (PE), perceived enjoyment (PEj), social influence (SI), and effort expectation (EE) of ET and behavior intention (BI)

2. To investigate the relationship between behavior intention (BI) and ET usage.

3. To investigate the relationship between Facilitating Conditions (FC) and ET usage.

4. To examine the moderating influence of University Type and Demographic Vaariables in the relationship among the antecedents of Behavior Intention (BI), Facilitating Conditions and ET usage.

3.3 Conceptualized Research Model

Following research model has been considered for the study

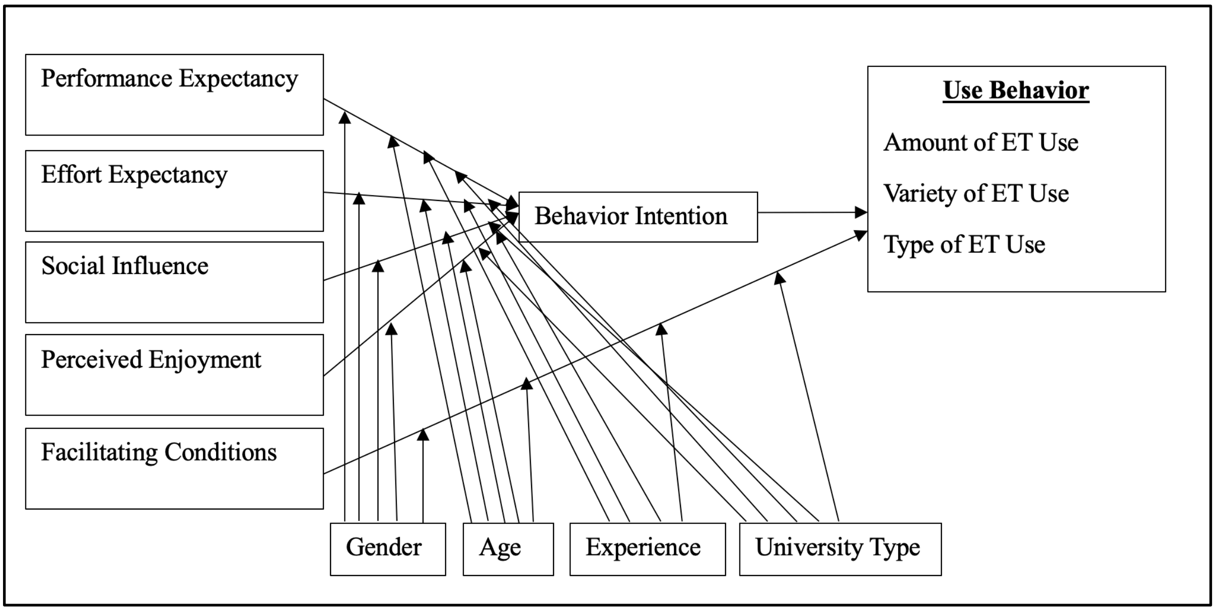

Fig 3.1: Proposed Research Model

The proposed research framework for the **Adoption of Educational Technology (ET)** among educators in India is adapted from the **Unified Theory of Acceptance and Use of Technology (UTAUT)** model. This theoretical model was initially proposed by Venkatesh et al. (2003) to understand technology adoption and usage behavior in organizational and individual contexts. In this study, the framework incorporates essential UTAUT constructs—**Performance Expectancy (PE)**, **Effort Expectancy (EE)**, **Social Influence (SI)**, **Perceived Enjoyment (PEj)/ Hedonic Motivation (HM)** and **Facilitating Conditions (FC)**—along with additional moderating variables like **Gender**, **Age**, **Experience**, and **University Type** to predict **Behavior Intention** and subsequent **Use Behavior** of ET.

3.4 Key Constructs and Their Relationships

3.4.1. Performance Expectancy (PE):

PE refers to the degree to which individuals believe that using a technology will enhance their job performance (Venkatesh et al., 2012). In the context of ET, educators perceive ET tools as valuable in improving teaching effectiveness, learning outcomes, and instructional efficiency. A positive belief in the usefulness of ET motivates educators to form intentions to adopt and use these tools.

3.4.2 Effort Expectancy (EE):

EE relates to the perceived ease of use of the technology (Venkatesh et al., 2003). When educators find EE intuitive and easy to operate, their Behavioral Intention (BI) to adopt ET increases. The framework suggests that simplicity in design and user-friendly interfaces of ET tools play a significant role in adoption.

3.4.3 Social Influence (SI):

SE refers to the pressure or encouragement an individual feels from people or groups they consider important, such as peers, supervisors, or influential figures, to adopt a particular technology. (Venkatesh et al., 2012).

3.4.4 Perceived Enjoyment (PEj)/ Hedonic Motivation (HM):

PEj/HM refers to the intrinsic motivation or pleasure derived from using technology (Thong et al., 2006). Educators who experience satisfaction and enjoyment from using ET tools are likely to develop favorable behavioral intentions toward technology adoption.

3.4.5 Facilitating Conditions (FC)

Facilitating conditions involve the resources, infrastructure, and support available to use the technology effectively (Venkatesh et al., 2003). For educators, facilitating conditions include access to training, technical support, and adequate IT infrastructure in educational institutions. These conditions enable smoother integration and continued use of ET.

3.4.6 Moderating Variables

The framework includes **four moderating variables—Gender**, **Age**, **Experience**, and **University Type**—that influence the relationships between the primary constructs and behavior intention or use behavior:

- **Gender**: Gender affects the intention of an individual to adopt technology (Khalid and Malah et al., 2023). Men tend to prioritize performance expectancy, whereas women place greater emphasis on effort expectancy and social influence (Venkatesh et al., 2003).
- **Age**: The relationship between effort expectancy, performance expectancy, and behavioral intention is moderated by age, with younger educators often being more receptive to adopting new technologies compared to older counterparts (Tarhini et al., 2016).
- **Experience**: Experience with similar technologies reduces perceived effort expectancy and strengthens the relationship between facilitating conditions and use behavior (Venkatesh et al., 2012).
- **University Type**: Institutional differences, such as private versus public universities, influence the availability of resources, training opportunities, and social norms around technology adoption.

3.4.7 Behavior Intention and Use Behavior

- **Behavioral Intention (BI)**: BI reflects educators' readiness and intention to adopt and use educational technology tools. The stronger the intention, the higher the likelihood of actual usage behavior (Ajzen, 1991; Venkatesh et al., 2003).
- **Use Behavior**: Use behavior is the actual adoption and utilization of ET tools by educators, measured in terms of the **amount**, **variety**, and **type** of technology used in teaching. Facilitating conditions and behavioral intention directly impact educators' actual technology adoption behavior.

3.5 Hypothesis Formulation

Following objectives have been considered for the study.

1. To investigate the relationship between performance expectancy (PE), perceived enjoyment (PEj), social influence (SI), and effort expectation (EE) of ET and behavior intention (BI)

2. To investigate the relationship between behavior intention (BI) and ET usage.

3. To investigate the relationship between Facilitating Conditions (FC) and ET usage.

4. To examine the moderating influence of University Type and Demographic Vaariables in the relationship among the antecedents of Behavior Intention (BI), Facilitating Conditions and ET usage.

The following Hypothesis are proposed for the Study

H1a. PE impacts the BI of educators to employ ET.

H1b. Gender, age, experience and university type will moderate the relationship between PE and BI.

H2a.EE impacts the BI of educators to use ET.

H2b. Gender, age, experience and university type will moderate the impact of EE on BI.

H3a.SI affects the BI of educators to use ET.

H3b.Gender, age, experience, and university type as moderate the impact of SI on BI.

H4a.PEj/HM impacts the BI of educators to use ET.

H4b. Gender, age, experience and university type moderate the effect of PEj/HM on BI.

H5a.FC impacts the usage of ET by educators.

H5b.Age, gender, experience and university type moderate the impact of FC on use behavior.

H6. BI influences educator’s use behavior of ET.

3.6 Research Design

The research design is the overarching strategy for obtaining answers to the research questions and resolving some of the difficulties encountered during the research process. The study design is tailored to the analysis's unique requirements. It is the organization of data collecting and analysis conditions in such a way that they maximize the value of the study while remaining economically feasible. According to Hagan (2000) and Fouche (2002), research design refers to "the study's plan or blueprint." A research design is a guideline that entails a strategy of data collecting selection.

This research is descriptive in nature, providing a comprehensive overview of the subject and realistically describing the characteristics of a situation, namely the adoption factors of ET among educators in state and central universities in India. To accomplish the research aims, descriptive research design has been adopted by employing - structural equation modelling - and multi group analysis on responses collected through a personal survey.

3.7 Research Method – Scope of Study

According to Leedy and Ormrod (2001), methodology refers to "the overall approach taken by the researcher in carrying out the research endeavor." The result was tabulated utilizing quantitative research mathematics methodologies, specifically, Excel, R, and Jamovi, which were utilized to examine the data.

This study uses quantitative survey technique to answer the research questions by testing the hypothesis and simultaneously tries to achieve the research objectives. Empirical data is collected from the sample respondents using online survey tools such as Google Forms and Microsoft Forms. These forms were shared through email to the sample respondents and the email ids of the respondents were compiled from the University websites. Only those Universities were considered which were available in the Consolidated List of all Universities -2021 Published by University Grants Commission (UGC).

3.8 Sample Design

3.8.1 Universe of Study

The faculty members working in Central Universities, State Universities, Private Universities and Deemed to be Universities in India constitute the universe of the study.

Table 3.1: Total number of Universities in the Country as on 17th May, 2021

Universities	**Total No.**
Private Universities	376
State Universities	426
Central Universities	54
Deemed to be Universities	125
Total	**981**

Source: Universities Grants Commission

3.8.2 Population of Study

The faculty members working in Central and State Universities in India constitute the population of the study. The UGC website does not provide any details about the number of staff members/educators about Deemed to be Universities and Private Universities, so they have not been considered.

Proportionate representation is given to each university type according to their actual numbers. The contact details of all the faculty members of each university from all the above-mentioned categories has been compiled. Those universities which have not published the contact details of the faculty members have been eliminated from population.

The break-up of the sample taken from Central, and State Universities is as follows where we are freezing upon a sample size of 1000 respondents.

* ***Note:*** The original sample size decided for the study was 354 based on Hair et al. (2010) but based on an expert suggestion given during the End Term Presentation, the sample size was increased to 1000 to make this study more representative of the population.

Table 3.2: Proportionate Sampling from Central and State Universities

	Central Universities	**State Universities**
Count of Universities	54	426
Total Count of Educators	9896	67536
Sample Size	128	872

3.8.3 Sample Technique, Sampling Size and Unit

Stratified random sampling technique is adopted for the conduct of the current study. Proportionate representation is given to each university type according to their actual numbers. The contact details of all the faculty members of each university from all the above-mentioned categories has been compiled. Those universities which have not published the contact details of the faculty members have been eliminated from population.

The break-up of the sample taken from Central, and State Universities is as follows where we are freezing upon a sample size of 1000 respondents.

- **Sample from Central Universities:** (Σ Faculty from Central Universities / Σ Faculty from Central and State Universities) *1000 = 128
- **Sample from State Universities** = (Σ Faculty from State Universities / Σ Faculty from Central and State Universities) *1000 = 872

Sample Unit: The faculty members working in Central and State Universities define as sample unit.

3.9. Instrument

The most important part of any survey is the questionnaire. The survey results depend a lot on the questions asked in the questionnaire.

Table 3.3: Description of Survey Sections in the Questionnaire

Section	**Description**	**Reference**	**Number of Question Items**
1.	Introduction to the study by explaining the purpose and objectives of the study.		NA
2.	This section collects some general and demographic information about the respondents.		6
3.	This section deals with adapted items from the UTAUT study related to the construct of PE	Venkatesh, et.al., (2003)	8
4.	This section deals with adapted items from the UTAUT study related to the construct of EE	Venkatesh, et.al., (2003)	5
5.	This section deals with adapted items from the UTAUT study related to the construct of SI	Venkatesh, et.al., (2003)	7
6.	This section deals with adapted items from the UTAUT study related to the construct of PEj/HM	Venkatesh, et.al., (2003)	8
7.	This section deals with adapted items from the UTAUT study related to the construct of FC	Venkatesh, et.al., (2003)	7
8.	This section deals with adapted items from the UTAUT study related to the construct of BI	Venkatesh, et.al., (2003)	6
9.	This section deals with adapted items from the actual study of Grant Blank and Darja Groselj (2014) related to the construct of Amount of Technology Use	Blank, G., & Groselj, D. (2014).	17
10.	This section deals with adapted items from the actual study of Grant Blank and Darja Groselj (2014) related to the construct of Variety of Technology Use	Blank, G., & Groselj, D. (2014).	17
11.	This section deals with adapted items from the actual study of Grant Blank and Darja Groselj (2014) related to the construct of Type of Technology Use	Blank, G., & Groselj, D. (2014).	15

All the constructs were captured using statements on a 5-point Likert Scale. The statements were constructed using both positive and negative words to minimize acquiescent bias.

3.10. Content Validation and Content Validity Index Calculation

The validity of anything may essentially be determined by looking at five pieces of evidence: the content, the response process, the internal structure, the link with other factors, and the result. To define "the extent to which features of a survey instrument, such as a survey questionnaire, is relevant to and indicative of the idea for a specific survey," is a common definition of "content validity." In most cases, the variable that is being sought to be measured is meant to be understood as the construct. If the components of the instrument are suited for the intended construct of the survey, then one may say that the instrument is relevant or suitable. On the other hand, the representativeness of a survey instrument is defined as the degree to which its components are proportionate to the aspects of the constructs that are being investigated or measured. Even though there are two different elements of content validity, one of the characteristics that is more generally utilized and recognized to evaluate content validity is the relevance of an evaluation instrument that was proposed by Davis, 1989. While doing research of any kind, it is of the utmost significance to determine whether or not an instrument has content validity. In spite of the fact that the other indices of validity are adequate, any conclusions that are drawn from an instrument that has an insufficient level of content validity are always susceptible to scepticism.

3.10.A Definitions Used in Content Validity

CVI – Content Validity Index

I-CVI – Item-Level Content Validity Index

S-CVI – Scale – Level Content Validity Index

UA – Universal Agreement

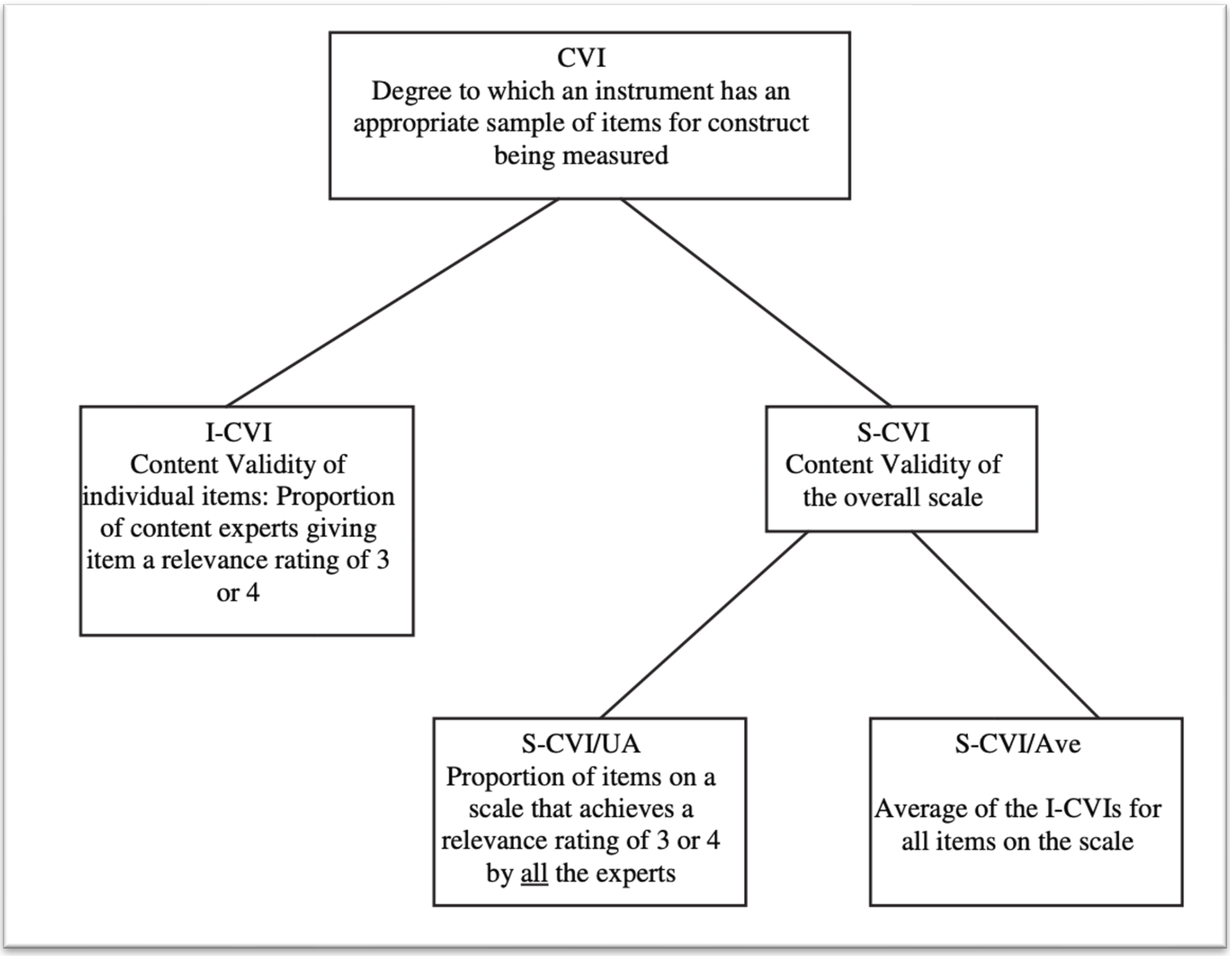

Figure 3.2: Definitions of Content Validity Terms

3.10.B Content Validity Procedure

The following six steps were followed for content validation:

Step-1: Preparation of Content Validation Form

The content validation form sets appropriate expectations and understanding for the experts in the review panel. They clearly understand exactly what is expected from them. Clear instructions were provided to the reviewers as follows:

Dear Experts,

I am a research scholar at Lovely Professional University. My research topic is **User Acceptance, Behavior Intention and Use Behavior Towards Education Technology Among Educators.** The objective of the work is to study the Behavioral Intentions and actual use behavior of EdTech by university teachers. In addition, I am also analyzing the mediating effects of BI on Use Behavior.

This instrument contains 9 constructs and 90 items related to Education Technology Adoption adapted from UTAUT framework, a study adapted from Venkatesh et al., 2003. I solicit your feedback on the degree of relevance of each item to be measured. Kindly base your review on the definition and relevant terminology provided to you. You are requested to be as constructive and objective as possible and use the following rating scale.

Degree of Relevance

1= the item is not relevant to the construct being measured

2 = the item is somewhat relevant to the construct being measured

3 = the item is quite relevant to the construct being measured

4 = the item is highly relevant to the construct being measured

Construct-wise definition was provided to experts to ensure the objective and constructive evaluation of scale item by subject matter expert.

Step-2: Selection of Panel of Experts for Review

A panel of experts was chosen based on their level of competence in the subject area. The profiles of experts on Research Gate were analyzed, and the panel was established based on their prior work with the UTAUT framework and their research interest in ET. The Table 6.4 highlights the suggested number of experts and their impact on CVI cutoff values.

Table 3.4: Suggested Number of Experts for CVI

Number of Experts	CVI Cut-offs	Source
2	≥0.80	Davis (1992)
3-5	1	Polit & Beck (2006); Polit et al., (2007)
≥6	≥0.83	Polit & Beck (2006); Polit et al., (2007)
6-8	≥0.83	Lynn (1986)
≥9	≥0.78	Lynn (1986)

According to this table, the minimal number of experts required for content validity is two, but most popular studies in this field propose at least six experts to review the questionnaire. With a minimum of six experts and the researcher's experience, it can be reasonably stated that anywhere between seven and ten experts is optimal for content validity. The current study employed inputs from seven experts to determine the content validity.

Step-3: Conducting Content Validation

Content validation can be performed in a f2f or non-f2f mode. The COVID Lockdown served as a deterrent, and content validation was handled remotely. In the context of the current study, a non-face-to-face technique is utilized, the selected experts receive an online content validation review form with clear instructions on how to perform the content validation exercise, which involves examining constructs and items, rating objects, and computing the CVI indices. The response rate and time required to gather criticisms from each expert were incredibly slow in this instance, demanding several reminders and requests.

Step-4: Review of Constructs and Items

While sharing the content validation form, it is critical that the constructs are well stated to avoid any ambiguity. There is no place for the expert reviewer's subjective judgement. The experts are then asked to examine the constructs objectively considering the stated definitions. The experts are asked to assess the constructs critically and objectively and to submit their scores. Following that, experts are asked to critique each construct to increase its relevance for the current study. All comments are then included to help enhance the constructs and succeeding items.

Step-5: Providing Each Item with a Score

After the experts complete their review, they are asked to assign a score to each item in the questionnaire using the supplied scale. After assessing each item separately, the experts are asked to report their scores to the researcher.

Step-6: Calculating CVI

Two types of CVIs are usually calculated; in which I-CVI is for item wise and S-CVI is for scale wise.

Before the calculation of CVIs is undertaken, the relevance rating provided by experts if coded as follows:

- Relevance rating by experts is 3 or 4, then it is coded as 1
- Relevance rating by experts is 1 or 2, then it is coded as 0

3.11. CVI Calculations

3.11.A Performance Expectancy

Table 3.5: CVI Calculations of Performance Expectancy

	Expert-1	Expert-2	Expert-3	Expert-4	Expert-5	Expert-6	Expert-7		Experts in Agreement	I-CVI	UA
Item	*Performance Expectancy*										
Q1: I find Education Technology useful within my teaching assignments	1	1	1	1	1	1	1		7	1	1
Q2: Using Education Technology enhances my effectiveness as a teacher	1	1	1	1	1	1	1		7	1	1
Q3: Through using Education Technology, I increase my chances of receiving good student feedback	1	1	1	1	1	1	1		7	1	1
Q4: I find Education technology useful in my day to day activities	1	1	1	1	1	1	1		7	1	1
Q5: Using Education Technology increases my chances of achieving things that are important to me.	1	1	1	1	1	1	1		7	1	1
Q6: Using technology in classroom helps me accomplish things more quickly	1	0	1	0	1	0	1		4	0.57	0
Q7: Using technology in my day to day classroom activities increases my productivity	0	1	1	1	0	0	0		3	0.43	0
									S-CVI/Ave (Based on I-CVI)	0.86	
Proportion Relevance	0.86	0.86	1.00	0.86	0.86	0.71	0.86		S-CVI/Ave (Based on Proportion Relevance)	0.86	
	Average proportion of items judged as relevance across the 7 experts							0.86	S-CVI/UA		0.71

3.11.B Effort Expectancy

Table 3.6: CVI Calculations of Effort Expectancy

	Expert-1	Expert-2	Expert-3	Expert-4	Expert-5	Expert-6	Expert-7		Experts in Agreement	I-CVI	UA
Item	*Effort Expectancy*										
Q1: I find Education Technology clear and understandable	1	1	1	1	1	1	1		7	1	1
Q2: It is easy for me to become skilful at using Education Technology	1	1	1	1	1	1	1		7	1	1
Q3: I find Education Technology easy to use	1	1	1	1	1	1	1		7	1	1
Q4: Learning to work with Education Technology is easy	1	1	1	1	1	1	1		7	1	1
Q5: Learning to use Education Technology products is easy for me.	1	1	0	1	1	1	0		5	0.714	0
									S-CVI/Ave (Based on I-CVI)	0.94	
Proportion Relevance	1.00	1.00	0.80	1.00	1.00	1.00	0.80		S-CVI/Ave (Based on Proportion Relevance)	0.94	
	Average proportion of items judged as relevance across the 7 experts							**0.94**	S-CVI/UA		0.80

3.11.C Perceived Enjoyment

Table 3.7: CVI Calculations of Perceived Enjoyment

	Expert-1	Expert-2	Expert-3	Expert-4	Expert-5	Expert-6	Expert-7		Experts in Agreement	I-CVI	UA
Item	*Perceived Enjoyment*										
Q1: Using education technology provides me with a lot of enjoyment	1	1	1	1	1	1	1		7	1	1
Q2: I enjoy using education technology	1	1	1	1	1	1	1		7	1	1
Q3: The process of using education technology is enjoyable	1	1	1	1	1	1	1		7	1	1
Q4: While using education technology, I experience pleasure	1	1	1	1	1	1	1		7	1	1
Q5: Overall, I believe education technology is playful	1	1	1	1	1	1	1		7	1	1
Q6: It would be fun to use education technology	1	0	1	0	1	0	1		4	0.57	0
Q7: I don't get bored while using education technology	0	1	1	1	0	0	0		3	0.43	0
Q8: Education technology makes my leisure time more fun	1	1	1	1	0	0	0		4	0.57	0
									S-CVI/Ave (Based on I-CVI)	0.82	
Proportion Relevance	0.88	0.88	1.00	0.88	0.75	0.63	0.75		S-CVI/Ave (Based on Proportion Relevance)	0.82	
	Average proportion of items judged as relevance across the 7 experts							**0.82**	S-CVI/UA		0.63

3.11.D. Social Influence

Table 3.8: CVI Calculations of Social Influence

Item	*Social Influence*										
Q1: My colleagues think that I should use Education Technology more innovatively	1	1	1	1	1	1	1		7	1	1
Q2: Colleagues, who are important to me, think that I should use Education Technology	1	1	1	1	1	1	1		7	1	1
Q3: The educational council of my programme supports the use of Education Technology	1	1	1	1	1	1	1		7	1	1
Q4: In general, the university supports the use of Education Technology	1	1	1	1	1	1	1		7	1	1
Q5: In general, the faculty supports the use of Education Technology	1	1	1	1	1	1	1		7	1	1
Q6: The chairman of my educational council thinks that I should use Education Technology	1	0	1	1	1	0	1		5	0.71	0
Q7: People who influence my behavior think that I should use Technology in my classroom	0	1	1	1	1	0	0		4	0.57	0
									S-CVI/Ave (Based on I-CVI)	0.90	
Proportion Relevance	0.86	0.86	1.00	1.00	1.00	0.71	0.86		S-CVI/Ave (Based on Proportion Relevance)	0.90	
	Average proportion of items judged as relevance across the 7 experts							**0.90**	S-CVI/UA		0.71

3.11.E. Facilitating Conditions

Table 3.9: CVI Calculations of Facilitating Conditions

Item	***Facilitating Conditions***										
Q1: I have the resources necessary to use Education Technology	1	1	1	1	1	1	1		7	1	1
Q2: Education Technology is compatible with the way I teach	1	1	1	1	1	1	1		7	1	1
Q3: A specific person is available for assistance with difficulties when using Education Technology	1	1	1	1	1	1	1		7	1	1
Q4: I have the knowledge necessary to use Education Technology	1	1	1	1	1	1	1		7	1	1
Q5: I feel that I can make informed decisions about which tools/resources to use within Education Technology	1	1	1	1	1	1	1		7	1	1
Q6: I feel that I can fully take advantage of Education Technology thanks to the resources within Education Technology	1	0	1	0	1	1	1		5	0.71	0
Q7: I have looked for tools outside of Education Technology so that I can further innovate with my teaching through technology	0	1	1	1	1	0	0		4	0.57	0
									S-CVI/Ave (Based on I-CVI)	0.90	
Proportion Relevance	0.86	0.86	1.00	0.86	1.00	0.86	0.86		S-CVI/Ave (Based on Proportion Relevance)	0.90	
	Average proportion of items judged as relevance across the 7 experts							**0.90**	S-CVI/UA		0.71

3.11.F. Behavior Intention

Table 3.10: CVI Calculations of Behavior Intention

	Expert-1	Expert-2	Expert-3	Expert-4	Expert-5	Expert-6	Expert-7		Experts in Agreement	I-CVI	UA
Item	*Behavior Intention*										
Q1: I intend to use technology in my classroom in the future	1	1	1	1	1	1	1		7	1	1
Q2: I will always try to use Education Technology in my day to day activities in my classroom	1	1	1	1	1	1	1		7	1	1
Q3: I plan to use education technology frequently	1	1	1	1	1	1	1		7	1	1
Q4: Among my peers, I am the first one to use any new technology	1	1	1	1	1	1	1		7	1	1
Q5: When I hear about a new technology, I often find an excuse to use it	1	1	1	1	1	1	1		7	1	1
Q6: Assuming that I have access to Education Technology, I intend to use it.	1	0	1	0	1	1	1		5	0.71	0
									S-CVI/Ave (Based on I-CVI)	0.95	
Proportion Relevance	1.00	0.83	1.00	0.83	1.00	1.00	1.00		S-CVI/Ave (Based on Proportion Relevance)	0.95	
	Average proportion of items judged as relevance across the 7 experts							0.95	S-CVI/UA		0.83

3.11.G. Amount of Use

Table 3.11: CVI Calculations of Amount of Use

	Expert-1	Expert-	Expert-3	Expert-4	Expert-5	Expert-6	Expert-7		Experts in Agreement	I-CV	UA
Item	*Amount of Technology Usage*										
Q1: I spend several hours per day using virtual reality environments in	1	1	1	1	1	1	1		7.00	1.00	1.00
Q2: I spend several hours per day using digital databases	1	1	1	1	1	1	1		7.00	1.00	1.00
Q3: I spend several hours per day using digital	0	0	0	0	0	1	1		2.00	0.29	0.00
Q4: I spend several hours per day using online media repositories	1	1	1	1	1	1	1		7.00	1.00	1.00
Q5: I spend several hours per day using online survey tools	1	1	1	1	1	1	1		7.00	1.00	1.00
Q6: I spend several hours per day using video and sound recording technologies for preparing	1	1	1	1	1	1	1		7.00	1.00	1.00
Q7: I spend several hours per day using data analysis software	1	1	1	1	1	1	1		7.00	1.00	1.00
Q8: I spend several hours per day using word processing technologies such as MS Word	1	1	1	1	1	1	1		7.00	1.00	1.00
Q9: I spend several hours per day using video conferencing software to interact with students	0	0	0	0	1	1	0		2.00	0.29	0.00
Q10: I spend several hours per day using quiz creation software and tools to make my lessons engaging and interactive	1	1	1	1	1	1	1		7.00	1.00	1.00
Q11: I spend several hours per day using collaboration tools such as Google classroom	1	1	1	1	0	1	0		5.00	0.71	0.00
Q12: I spend several hours per day using simulation games to make my lessons engaging and practical	0	1	1	1	1	1	1		6.00	0.86	0.00
Q13: I spend several hours per day using computer assisted design software	1	0	1	1	1	1	1		6.00	0.86	0.00
Q14: I spend several hours per day using visualization tools such as Tableau and Excel etc.	1	1	1	1	1	1	1		7.00	1.00	1.00
Q15: I spend several hours per day using drawing and painting technologies to make my lessons realistic	1	1	1	1	0	1	1		6.00	0.86	0.00
Q16: I spend several hours per day using animation technologies such as Powtoon and Scratch to make my lessons visually appealing	1	1	1	1	1	0	1		6.00	0.86	0.00
Q17: I spend several hours per day using Multimedia composition technologies such as Adobe Spark, Movie Maker etc. to add zing to my lessons	1	1	1	0	1	1	1		6.00	0.86	0.00
									S-CVI/Ave (Based on I-CVI)	0.89	
Proportion Relevance	0.86	0.86	0.86	0.86	0.86	1	1		S-CVI/Ave (Based on Proportion	0.90	
	Average proportion of items judged as relevance across the 7 expert							0.89	S-CVI/UA		0.53

3.11.H. Variety of Use

Table 3.12: CVI Calculations of Variety of Use

	Expert-1	Expert-2	Expert-3	Expert-4	Expert-5	Expert-6	Expert-7		Experts in Agreement	I-CVI	UA
Item	*Variety of Technology Usage*										
Q1: I often use virtual reality environments in teaching	1	1	1	1	1	1	1		7.00	1.00	1.00
Q2: I often use digital databases	1	1	1	1	1	1	1		7.00	1.00	1.00
Q3: I often use digital libraries	0	0	0	0	0	1	1		2.00	0.29	0.00
Q4: I often use online media repositories	1	1	1	1	1	1	1		7.00	1.00	1.00
Q5: I often use online survey tools	1	1	1	1	1	1	1		7.00	1.00	1.00
Q6: I often use video and sound recording technologies for preparing my lectures	1	1	1	1	1	1	1		7.00	1.00	1.00
Q7: I often use data analysis software	1	1	1	1	1	1	1		7.00	1.00	1.00
Q8: I often use word processing technologies such as MS Word	1	1	1	1	1	1	1		7.00	1.00	1.00
Q9: I often use video conferencing software to interact with students	0	0	0	0	1	1	0		2.00	0.29	0.00
Q10: I often use quiz creation software and tools to make my lessons engaging and interactive	1	1	1	1	1	1	1		7.00	1.00	1.00
Q11: I often use collaboration tools such as Google classroom	1	1	1	1	0	1	0		5.00	0.71	0.00
Q12: I often use simulation games to make my lessons engaging and practical	0	1	1	1	1	1	1		6.00	0.86	0.00
Q13: I often use computer assisted design software	1	0	1	1	1	1	1		6.00	0.86	0.00
Q14: I often use visualization tools such as Tableau and Excel etc.	1	1	1	1	1	1	1		7.00	1.00	1.00
Q15: I often use drawing and painting technologies to make my lessons realistic	1	1	1	1	1	1	1		7.00	1.00	1.00
Q16: I often use animation technologies such as Powtoon and Scratch to make my lessons visually appealing	1	1	1	1	1	1	1		7.00	1.00	1.00
Q17: I often use Multimedia composition technologies such as Adobe Spark, Movie Maker etc. to add zing to my lessons	1	1	1	1	1	1	1		7.00	1.00	1.00
									S-CVI/Ave (Based on I-CVI)	0.97	
Proportion Relevance	0.86	0.86	0.86	0.86	0.86	1	1		S-CVI/Ave (Based on Proportion	0.90	
	Average proportion of items judged as relevance across the 7 experts							0.94	S-CVI/UA		0.71

3.11.I. Type of Use

Table 3.13: CVI Calculations of Type of Use

	Expert-1	Expert-2	Expert-3	Expert-4	Expert-5	Expert-6	Expert-7		Experts in Agreement	I-CVI	UA
Item	*Type of Technology Usage*										
Q1: I often use technology for Inquiry	1	1	1	1	1	1	1		7.00	1.00	1.00
Q2: I often use Education Technology for communication	1	1	1	1	1	1	1		7.00	1.00	1.00
Q3: I often use technology for construction and problem solving	0	0	0	0	0	1	1		2.00	0.29	0.00
Q4: I often use technology for knowledge representation	1	1	1	1	1	1	1		7.00	1.00	1.00
Q5: I often use technology for assessment	1	1	1	1	1	1	1		7.00	1.00	1.00
Q6: I often use technology for classroom efficiency	1	1	1	1	1	1	1		7.00	1.00	1.00
Q7: I often use technology for classroom management	1	1	1	1	1	1	1		7.00	1.00	1.00
Q8: I often use technology for classroom response system	1	1	1	1	1	1	1		7.00	1.00	1.00
Q9: I often use technology for collaboration tools	0	0	0	0	1	1	0		2.00	0.29	0.00
Q10: I often use technology for curriculum platforms	1	1	1	1	1	1	1		7.00	1.00	1.00
Q11: I often use technology for grading and attendance	1	1	1	1	0	1	0		5.00	0.71	0.00
Q12: I often use technology for lesson planning	0	1	1	1	1	1	1		6.00	0.86	0.00
Q13: I often use technology for professional learning	1	0	1	1	1	1	1		6.00	0.86	0.00
Q14: I often use technology for presentation tools	1	1	1	1	1	1	1		7.00	1.00	1.00
Q15: I often use technology for special education	1	1	1	1	1	1	1		7.00	1.00	1.00
									S-CVI/Ave (Based on I-CVI)	0.95	
Proportion Relevance	0.86	0.86	0.86	0.86	0.86	1	1		S-CVI/Ave (Based on Proportion	0.90	
	Average proportion of items judged as relevance across the 7 experts							**0.93**	S-CVI/UA		0.67

As a follow-up to the content validity tested using I-CVI metric, the following actions were taken on the instrument items:

3.12. Action Taken After CVI Calculations

3.12.A. Performance Expectancy

Table 3.14: Action Taken on Items of Construct Performance Expectancy

Construct	Item	I-CVI	Action
Performance Expectancy	Q1	1	Retained
	Q2	1	Retained
	Q3	0.71	**Dropped**
	Q4	1	Retained
	Q5	1	Retained
	Q6	0.57	**Dropped**
	Q7	0.43	**Dropped**

100% agreement of experts is mandatory for an item to be retained in the questionnaire, so wherever, the I-CVI is less than 1, those items have been dropped from the instrument(Polit & Beck, 2006).

3.12.B. Effort Expectancy

Table 3.15: Action Taken on Items of Construct Effort Expectancy

Construct	Item	I-CVI	Action
Effort Expectancy	Q1	1	Retained
	Q2	1	Retained
	Q3	1	Retained
	Q4	1	Retained
	Q5	0.71	**Dropped**

100% agreement of experts is mandatory for an item to be retained in the questionnaire, so wherever, the I-CVI is less than 1, those items have been dropped from the instrument(Polit & Beck, 2006).

3.12.C. Social Influence

Table 3.16: Action Taken on Items of Construct Social Influence

Construct	Item	I-CVI	Action
Social Influence	Q1	1	Retained
	Q2	1	Retained
	Q3	0.71	**Dropped**
	Q4	0.57	**Dropped**
	Q5	1	Retained
	Q6	0.71	**Dropped**
	Q7	0.57	**Dropped**

100% agreement of experts is mandatory for an item to be retained in the questionnaire, so wherever, the I-CVI is less than 1, those items have been dropped from the instrument(Polit & Beck, 2006).

3.12.D. Perceived Enjoyment

Table 3.17: Action Taken on Items of Construct Perceived Enjoyment

Construct	Item	I-CVI	Action
Perceived Enjoyment	Q1	1	Retained
	Q2	0.71	**Dropped**
	Q3	1	Retained
	Q4	1	Retained
	Q5	1	Retained
	Q6	0.57	**Dropped**
	Q7	0.43	**Dropped**

100% agreement of experts is mandatory for an item to be retained in the questionnaire, so wherever, the I-CVI is less than 1, those items have been dropped from the instrument(Polit & Beck, 2006).

3.12.E. Facilitating Conditions

Table 3.18: Action Taken on Items of Construct Facilitating Conditions

Construct	Item	I-CVI	Action
Facilitating Conditions	Q1	1	Retained
	Q2	1	Retained
	Q3	0.71	**Dropped**
	Q4	0.57	**Dropped**
	Q5	1	Retained
	Q6	0.71	**Dropped**
	Q7	0.57	**Dropped**

100% agreement of experts is mandatory for an item to be retained in the questionnaire, so wherever, the I-CVI is less than 1, those items have been dropped from the instrument(Polit & Beck, 2006).

3.12.F. Behavior Intention

Table 3.19: Action Taken on Items of Construct Behavior Intention

Construct	Item	I-CVI	Action
Facilitating Conditions	Q1	1	Retained
	Q2	1	Retained
	Q3	0.71	**Dropped**
	Q4	0.71	**Dropped**
	Q5	1	Retained
	Q6	0.71	**Dropped**

100% agreement of experts is mandatory for an item to be retained in the questionnaire, so wherever, the I-CVI is less than 1, those items have been dropped from the instrument(Polit & Beck, 2006).

3.12.G. Amount of Technology Use

Table 3.20: Action Taken on Items of Amount of Technology Use

Construct	Item	I-CVI	Action
Amount of Technology Use	Q1	1	Retained
	Q2	1	Retained
	Q3	0.29	**Dropped**
	Q4	1	Retained
	Q5	1	Retained
	Q6	0.71	**Dropped**
	Q7	1	Retained
	Q8	1	Retained
	Q9	0.29	**Dropped**
	Q10	1	Retained
	Q11	0.71	**Dropped**
	Q12	0.71	**Dropped**
	Q13	0.71	**Dropped**
	Q14	1	Retained
	Q15	0.71	**Dropped**
	Q16	0.71	**Dropped**
	Q17	0.71	**Dropped**

100% agreement of experts is mandatory for an item to be retained in the questionnaire, so wherever, the I-CVI is less than 1, those items have been dropped from the instrument(Polit & Beck, 2006).

3.12.H. Variety of Technology Use

Table 3.21: Action Taken on Items of Variety of Technology Use

Construct	Item	I-CVI	Action
Variety of Technology Use	Q1	1	Retained
	Q2	1	Retained
	Q3	0.29	**Dropped**
	Q4	1	Retained
	Q5	0.71	**Dropped**
	Q6	1	**Dropped**
	Q7	0.71	**Dropped**
	Q8	1	Retained
	Q9	0.29	**Dropped**
	Q10	1	Retained
	Q11	0.71	**Dropped**
	Q12	0.71	**Dropped**
	Q13	0.71	**Dropped**
	Q14	1	Retained
	Q15	0.71	**Dropped**
	Q16	1	Retained
	Q17	0.71	**Dropped**

100% agreement of experts is mandatory for an item to be retained in the questionnaire, so wherever, the I-CVI is less than 1, those items have been dropped from the instrument(Polit & Beck, 2006).

3.12.I. Type of Technology Use

Table 3.22: Action Taken on Items of Type of Technology Use

Construct	Item	I-CVI	Action
Type of Technology Use	Q1	0.71	**Dropped**
	Q2	1	Retained
	Q3	0.29	**Dropped**
	Q4	1	Retained
	Q5	1	Retained
	Q6	0.71	**Dropped**
	Q7	1	Retained
	Q8	1	Retained
	Q9	0.29	**Dropped**
	Q10	1	Retained
	Q11	0.71	**Dropped**
	Q12	0.71	**Dropped**
	Q13	0.71	**Dropped**
	Q14	1	Retained
	Q15	1	Retained

100% agreement of experts is mandatory for an item to be retained in the questionnaire, so wherever, the I-CVI is less than 1, those items have been dropped from the instrument(Polit & Beck, 2006).

3.13. Pilot Study

3.13.A. Introduction

The pilot study is a crucial step in the research process, serving as a preliminary analysis to ensure the reliability and validity of the survey instruments and methodology. This study focused on assessing the adoption factors of Education Technology (ET) among educators in state and central universities in India. The primary objective was to refine the research instruments and methodology before the full-scale study.

3.13.B. Objectives of the Pilot Study

The pilot study aimed to:

1. Validate the reliability and stability of the scale items used in the survey.
2. Identify potential issues in the survey design and administration process.
3. Assess the feasibility of the research design and methodology.

3.13.C. Research Design and Methodology

The research design for the pilot study was tailored to address specific research questions and hypotheses related to the adoption of ET. The study utilized a quantitative survey technique, collecting empirical data from a sample of educators using online survey tools like Google Forms and Microsoft Forms.

3.13.D. Sampling Technique

A proportionate sampling method was employed, considering only central and state universities from the Consolidated List of Universities published by the University Grants Commission (UGC). The sampling frame excluded private and deemed universities due to the lack of available contact details for educators. The sample size for the pilot study was determined to be 100 educators, representing 10% of the total target sample size of 1000.

3.13.E. Data Analysis

The data collected from the pilot study were analyzed using statistical techniques to assess the reliability and validity of the survey items. This included checking for internal consistency using Cronbach's alpha and conducting exploratory factor analysis to confirm the construct validity of the questionnaire.

3.13.F. Findings from the Pilot Study

The pilot study provided valuable insights into the reliability and stability of the survey instruments. The results indicated that the questionnaire items were generally reliable, with Cronbach's alpha values exceeding the acceptable threshold of 0.70 for most constructs. The exploratory factor analysis confirmed the construct validity, with items loading appropriately on their respective factors.

3.13.G. Conclusion

The pilot study successfully validated the research instruments and methodology, providing a solid foundation for the full-scale study. The feedback from the pilot study participants and the statistical analysis of the data helped refine the questionnaire and sampling procedures, ensuring a robust and reliable research design.

3.14. Execution of Survey

3.14.1 Sample Selection

- From the list of faculties from Central Universities whose contacts are available, Random Number Generator Algorithm will be applied to it and a sample of 128 units will be picked from the list.

- From the list of faculties from State Universities whose contacts are available, Random Number Generator Algorithm will be applied to it and a sample of 872 units will be picked from the list.

3.14.2 Codes Used in R Programming to Generate the Sample

```
library(dplyr)
su=read.csv(file.choose(), header=T)
cu=read.csv(file.choose(), header=T)
set.seed(999)
state=sample_n(su, 872)
central=sample_n(cu,128)
```

Fig 3.3: Random Sampling from Central and State Universities

Here **“dplyr”** package is used which is a popular data manipulation package in R Programming. **“su”** is the dataset of State University Faculty email ids imported into R Programming environment and likewise **“cu”** is the Central University Faculty email ids imported into R Programming environment. **“state”** and **“central”** is the random sample of 872 and 128 generated respectively using the ***sample_n*** function of the ***dplyr*** package. The ***set.seed*** function of R programming helps to make the data reproducible, so that the random samples generated do not change every time we run the program.

Data collection is a pivotal phase in any research, and to assess the adoption of Educational Technology (ET) among educators in state and central universities in India, this phase was meticulously planned and executed. This section details the methodologies, instruments, and processes involved in collecting data for the study.

3.14.3 Data Collection Process

The data collection process for this study was meticulously designed to ensure a robust and representative sample of educators across **central universities** and **state universities** in India. Given the critical objective of investigating the adoption of educational technology (ET), a stratified random sampling technique was employed to capture diverse perspectives from educators in both types of institutions.

3.14.4 Pilot Survey and Response Rate Estimation

A pilot survey was initially conducted to estimate the response rate and test the effectiveness of the survey instrument. The pilot yielded a **response rate of 4%**, which served as a basis for determining the number of educators to whom the questionnaire needed to be sent in the main survey phase. A response rate of 4% aligns with similar studies where online surveys are used in educational technology adoption research (Baruch & Holtom, 2008).

To achieve a final sample size of **1000 valid responses**, the following calculation was applied:

$$\text{Required invitations} = \frac{\text{Desired responses}}{\text{Response rate}} = \frac{1000}{0.04} \approx 30000$$

Thus, approximately **30,000 educators** needed to be contacted.

3.14.5 Sampling Process

1. **Construction of the Contact List**:

   A comprehensive list of educators was compiled by systematically extracting publicly available contact details from university websites. Two separate lists were created to distinguish between educators from **central universities** and **state universities**.

2. **Stratified Random Sampling**:

   To ensure proportional representation, the sampling process followed a stratified approach. According to this method, the target sample size was divided into two strata:

   - **Central Universities**: 128 educators
   - **State Universities**: 872 educators

   This proportional division ensured that responses reflected the actual distribution of central and state universities in India, thereby improving the generalizability of the findings (Creswell & Creswell, 2018).

3. **Random Sampling and Response Collection**:
   - From each list (central and state universities), a random sample was generated using a random number generator to ensure impartiality (Saunders, Lewis, & Thornhill, 2019).
   - The process of random sampling continued until the **target number of responses** (128 for central universities and 872 for state universities) was achieved.
   - This iterative process accounted for non-responses and ensured the final sample met the study's requirements.

3.14.6 Justification for Sampling Design

The combination of stratified sampling and random sampling is well-suited for this study due to the following reasons:

- Stratified sampling ensures **representation** of both central and state universities, reflecting institutional diversity (Etikan & Bala, 2017).
- Random sampling eliminates selection bias and enhances the reliability of the collected data (Bryman & Bell, 2015).
- A systematic approach to data collection is critical when targeting a large population, as it maximizes efficiency and minimizes errors in sampling.

3.14.7 Survey Administration

The questionnaire was distributed electronically via email, which is a common and effective approach for large-scale studies in education (Evans & Mathur, 2018). The use of online surveys provided several advantages, including faster data collection, cost efficiency, and broader reach. Educators were assured of the confidentiality of their responses, and reminders were sent periodically to encourage participation and improve the response rate.

3.14.8 Data Cleaning

Data cleaning involved the removal of incomplete or invalid responses. Specifically, 160 responses were excluded due to missing demographic information or lack of experience with ET. An additional 78 responses were removed for similar reasons. This rigorous cleaning process resulted in a final dataset of 1000 valid responses for analysis.

3.14.9 Data Analysis Preparation

The cleaned data were prepared for analysis by coding the responses and inputting them into statistical software. This preparation was crucial for ensuring that the subsequent data analysis would be accurate and meaningful.

3.14.10 Conclusion

The data collection process for the study on ET adoption among educators was meticulously planned and executed. From designing a valid and reliable questionnaire to systematically distributing it and cleaning the collected data, each step was carefully managed to ensure the quality of the data.

CHAPTER-4

DATA ANALYSIS

4.1. Introduction

This section discusses the achievement of the research objectives, specifically the analysis and identification of the components that serve as antecedents to ET, followed by a description of the link between the antecedents. Various components of the extended UTAUT model were adopted and validated in the manner described below. According to Hinkin (1998), the complete process of research instrument development included 4 steps:

Step 1: Item pool generation

Step 2: Survey administration

Step 3: CFA to derive factor structure; and

Step 4: Validity assessment of factors (or constructs).

Steps 1 and 2, which concerned item generation and data collection, were covered in Chapter 3 (Research Methodology). The subsequent phases 3 and 4, which involve psychometric examination of the research instrument, are outlined in the parts that follow. The construct validity has been assessed using Confirmatory Factor Analysis. Using the SEM program Jamovi, the relationship between the thus obtained and validated constructs was clarified.

The reliability of the questionnaire was calculated using Cronbach's Alpha. This study's findings on educators' acceptance of ET systems were subjected to reliability and validity tests using Cronbach's Alpha, Composite Reliability, and Average Variance Extracted. The Variance Inflation Factor (VIF) of all tested items was below the recommended value of 5, as well as the tolerance value of 1. This indicates that the collinearity is minimal and that there is no risk of an inflated product variance. Based on these initial findings of knowledge, the variables for the study were selected.

To test the research hypotheses, this study employed structural equation modelling with the model-fitting program SEM. Due to the complexity of the variables and constructs being analyzed and the considerably large sample size of 1000, SEM was employed.

Over the course of nearly a century, numerous researchers have utilized factor analysis in numerous fields. Currently, confirmatory factor analysis is used to test the presence of theoretical constructs and is gaining considerable importance. It took the ambitious Karl Joreskorg until 1960 to fully develop the theory of confirmative factor analysis. In 1990, Goldberg also employed CFA to test the five-variable model pertinent to his research. This implementation eventually made way for additional development, and a more sophisticated version of a path model was created. Sewell Wright (1918), the biologist who developed the Path model, utilized animal behavior to test its validity(Polit & Beck, 2006). The path model constructs more complex models between the observed variables by employing the regression method and correlation coefficient. The path model subsequently experienced a setback, as econometricians discovered alternative meanings. SEM creates convergence of the path model and an analysis of the confirmatory element, paving the way for the ultimate advanced model. In addition, SEM is considered a second-generation statistical method for evaluating multiple variables and their interrelationships. As a result, the Coefficient of Determination (R^2) was calculated to determine the extent to which the independent variables contribute to educators' use of ET systems.

4.2. Demographic Analysis:

In the demographic section, the respondent's demographic distribution has been examined. The socio-demographic analysis includes the analysis of data collected in terms of gender, age, experience, academic Rank and university type. The results are presented in the following Table No.4.1

Table 4.1: Demographic Distribution of the Sample Respondents

Characteristic	Profile	Frequency	(%)
Gender	Male	693	69.3
	Female	307	30.7
Age	Younger (<40 yrs)	501	50.1
	Older (>=40 yrs)	499	49.9
Experience	1 – 5 years	396	39.6
	5 – 10 years	299	29.9
	10 – 15 years	192	19.2
	15 years and above	113	11.3
Academic Rank	Assistant Professor	905	90.5
	Associate Professor	27	2.7
	Professor	68	6.8
University Type	Central University	128	12.8
	State University	872	87.2

4.3. Construct Reliability and Validity

Construct reliability and validity are crucial components in any research, especially in ET adoption studies. These components ensure that the measurement instruments used in the study are both consistent and accurate, thereby validating the results. The following sections provide a detailed analysis of construct reliability and validity, using data from Table 4.2.

4.3.1.Reliability Assessment

Reliability refers to the consistency of a measurement instrument. It indicates the extent to which the instrument yields the same results under consistent conditions. One of the most common measures of reliability is Cronbach's Alpha (α), which assesses internal consistency. George (2011) provides the following rule of thumb for interpreting Cronbach's Alpha:

- $\alpha > 0.9$ – Excellent
- $\alpha > 0.8$ – Good
- $\alpha > 0.7$ – Acceptable
- $\alpha > 0.6$ – Questionable
- $\alpha > 0.5$ – Poor
- $\alpha < 0.5$ – Unacceptable

Table 4.2 presents the Cronbach's Alpha values for various constructs used in the study on educational technology adoption:

- Performance Expectancy (PE): 0.811
- Effort Expectancy (EE): 0.879
- Social Influence (SI): 0.783
- Perceived Enjoyment (PEj): 0.862
- Facilitating Conditions (FC): 0.893
- Amount of Use (AU): 0.950
- Variety of Use (VU): 0.957
- Type of Use (TU): 0.950
- Behaviour Intention (BI): 0.895

All these constructs have alpha values greater than 0.7, indicating acceptable to excellent reliability. This suggests that the measurement instruments used in the study are consistent and reliable.

4.3.2. Validity Assessment

Validity refers to the degree to which an instrument measures what it is supposed to measure. There are two main types of validity: convergent validity and discriminant validity.

4.3.2.A Convergent Validity

Convergent validity is achieved when items that are supposed to measure the same construct are highly correlated. Two key indicators of convergent validity are Composite Reliability (CR) and Average Variance Extracted (AVE).

4.3.2.B Composite Reliability (CR)

Composite Reliability (CR) evaluates the internal consistency of a construct. A CR value exceeding 0.70 is typically deemed acceptable. In this study, all constructs demonstrated CR values above this threshold, confirming their reliability.

4.4. Average Variance Extracted (AVE)

Average Variance Extracted (AVE) assesses the proportion of variance captured by a construct relative to the variance attributable to measurement error. An AVE value of 0.50 or higher suggests adequate convergent validity. In this research, AVE values for all constructs surpassed this acceptable limit, thereby supporting their convergent validity.

4.5. Factor Loadings (FL)

Factor loadings represent the correlations between observed variables and their underlying latent constructs. High factor loadings, generally above 0.70, indicate that the items are strong indicators of their respective constructs. In this study, all factor loadings exceeded this threshold, reinforcing the robust convergent validity of the measurement model.

4.6 Discriminant Validity

Discriminant validity evaluates whether concepts or measurements that should be unrelated are, indeed, unrelated. According to Fornell and Larcker (1981), discriminant validity is confirmed if the square root of the AVE for each construct exceeds the correlations between that construct and others. In this study, discriminant validity was assessed through Confirmatory Factor Analysis (CFA). The results indicated that each construct had sufficient discriminant validity, signifying that each construct was distinct and measured a unique aspect of ET adoption.

4.7 Confirmatory Factor Analysis (CFA)

CFA is employed to test the measurement model and validate the structure of constructs, using a theory-driven approach to evaluate relationships between latent variables and their observed indicators. In this study, CFA was conducted using the SEM program Jamovi. The results demonstrated that the measurement items were appropriately related to their respective latent variables, confirming the validity of the constructs.

CFA also provided fit indices to evaluate the model's fit, such as the Chi-Square test, Root Mean Square Error of Approximation (RMSEA), Goodness-of-Fit Index (GFI), and Comparative Fit Index (CFI). The results from these indices indicated a good fit for the measurement model, supporting the overall validity of the constructs.

Table 4.2: Construct Reliability and Validity

Items		α	FL
Performance Expectancy		0.811	
PE2	I find Education Technology useful within my teaching assignments		0.705
PE3	The use of Education Technology enables me to accomplish tasks quicker and more efficiently		0.732
PE4	Through using Education Technology, I increase my chances of receiving good student feedback		0.722
PE5	I find Education technology useful in my day-to-day activities		0.749
Effort Expectancy		0.879	
EE1	I find Education Technology clear and understandable		0.828
EE2	It is easy for me to become skilful at using Education Technology		0.820
EE3	I find Education Technology easy to use		0.829
EE4	Learning to work with Education Technology is easy		0.811
Social Influence		0.783	
SI1	My colleagues think that I should use Education Technology more innovatively		0.769
SI2	Colleagues, who are important to me, think that I should use Education Technology		0.760
SI5	In general, the faculty supports the use of Education Technology		0.740

Perceived Enjoyment		0.862	
PEj1	Using education technology provides me with a lot of enjoyment		0.805
PEj3	The process of using education technology is enjoyable		0.803
PEj4	While using education technology, I experience pleasure		0.823
PEj5	Overall, I believe education technology is playful		0.828
Facilitating Conditions		0.893	
FC2	Education Technology is compatible with the way I teach		0.802
FC3	A specific person is available for assistance with difficulties when using Education Technology		0.803
FC4	I have the knowledge necessary to use Education Technology		0.830
FC5	I feel that I can make informed decisions about which tools/resources to use within Education Technology		0.828
Amount of Use		0.950	
AU1	I spend several hours per day using virtual reality environments in teaching		0.895
AU2	I spend several hours per day using digital databases		0.892
AU4	I spend several hours per day using online media repositories		0.897
AU5	I spend several hours per day using online survey tools		0.896
AU7	I spend several hours per day using data analysis software		0.902
Variety of Use		0.957	

VU1	I often use virtual reality environments in teaching		0.900
VU2	I often use digital databases		0.887
VU4	I often use online media repositories		0.909
VU6	I often use video and sound recording technologies for preparing my lectures		0.896
VU8	I often use word processing technologies such as MS Word		0.902
Type of Use		0.950	
TU2	I often use Education Technology for communication		0.893
TU4	I often use technology for knowledge representation		0.904
TU5	I often use technology for assessment		0.893
TU7	I often use technology for classroom management		0.899
TU8	I often use technology for classroom response system		0.900
Behaviour Intention		0.895	
BI1	I intend to use ET in the next 6 months		0.889
BI2	I predict that I would use ET in the next 6 months		0.870
BI5	I plan to use ET in the next 6 months		0.878

4.8 Validity Assessment of the Factors through Confirmatory Factor Analysis

Validity refers to "the ability of an instrument to measure what it claims to measure." There are two essential forms of validity: convergent validity and discriminant validity. Validity assessment involves evaluating construct reliability and construct validity through psychometric examination of the scale. Prior to assessing the structural relationships between proposed constructs, Confirmatory Factor Analysis (CFA) must be conducted. CFA is a theory-driven method used to evaluate theoretical relationships between latent and observable variables (Schreiber, 2006). This method examines the dimensionality and appropriateness of measurement items related to latent variables (Anderson, 1988). Results from a first-order CFA or a full-measurement model are used to evaluate composite reliability and establish construct validity. Constructs, which are "abstract variables not directly observed," are measured using appropriate indicators, or "manifest variables." Construct validity is a comprehensive term assessing the validity or adequacy of the indicator items used to test it (Nunnally, 1994). The goal is to ensure items represent the construct adequately.

In this study, construct validity was tested using convergent and discriminant validity (Hair, 2010). Construct validation aims to confirm that constructs are conceptually distinct from each other and do not have overlapping meanings. Items within the same construct should be correlated, indicating they converge on their respective construct, known as "convergent validity." Additionally, items must show lower association with measures related to other constructs, known as "discriminant validity" (Cronbach, 1955).

4.9 Establishing Construct Validity (Convergent and Discriminant Validity)

To verify the a priori factor structure of the extracted components, the nine resulting factors underwent CFA using Jamovi software. Since reliability is a prerequisite for validity, it was established first, followed by the evaluation of discriminant and convergent validity. The following sections outline the steps for analyzing the dependability and validity of the study variables.

4.10 Measurement Model (CFA)

Specific measurement models describe the relationship between latent variables and observed variables (Hair et al., 2006). The accuracy of defining a latent variable depends on how closely it relates to its indicators. CFA assesses the connection between proposed constructs and their measuring items (Khine, 2013). In this study, observable variables or measurement items are reflective, with arrows pointing from latent factors to measured items, indicating correlated measurements. CFA determines both discriminant and convergent validity (Fornell & Larcker, 1981). According to Fornell & Larcker (1981), the following criteria were applied to assess construct reliability and discriminant validity:

1. Standardized loading estimates for all indicators should be significant and greater than 0.5; ideally, they should exceed 0.7.

2. Each construct should have a minimum composite reliability (CR) rating of 0.70. However, for exploratory studies, this number may fall below 0.7 (Raykov, 1997). Bagozzi & Philips (1982) suggest a criterion of 0.6. CR can be computed as follows:

$$CR = \frac{(\sum \text{Standardized Loadings})^2}{(\sum \text{Standardized Loadings})^2 + \sum \varepsilon_j}$$

where standardized loadings are obtained from the output and ε_j is the measurement error for each indicator (Hair, 2016).

3. Average Variance Extracted (AVE) measure's reliability by reflecting the overall variance observed in variables attributable to the latent construct. AVE should exceed the measurement error margin, indicating that 50% of the variance in observed variables is accounted for by the construct and not by measurement errors. AVE is computed as follows:

$$AVE = \frac{\sum(\text{Standardized Loadings}^2)}{(\sum \text{Standardized Loadings})^2 + \sum \varepsilon_j}$$

4. Convergent validity requires the average variance explained by the construct to be less than the construct's overall reliability.

5. The sum of AVE values for all constructs should be larger than the sum of their Maximum Shared Variance (MSV) and Average Shared Variance (ASV), ensuring discriminant validity.

In this study, CR and AVE were used as measures of convergent validity (Fornell & Larcker, 1981). Joreskog's CR, developed in 1974, measures the consistency of a set of measurements. Nunnally (1994) deems a CR value between 0.7 and 0.9 satisfactory, while Bagozzi & Philips (1982) consider a CR value of 0.6 or higher acceptable. According to Hair et al. (2010), CR values over 0.60 are acceptable. AVE, another measure of convergent validity, is the grand mean value of the squared loadings of indicators associated with the construct (Hair, 2016). An AVE value over 0.50 indicates sufficient convergent validity.

4.11 Evaluating Measurement Model Fit

Within the measurement model, the covariance among all factors (variables or constructs) is assessed, known as "pooled CFA." Pooled CFA is more efficient and time-saving than evaluating each construct individually and addresses model identification issues. The model is assessed using fit indices, standardized regression weights, and the statistical significance of each indicator. AVE, CR, and maximum shared variance are calculated using standardized regression weights and correlation values between latent constructs.

4.12 Model Fit Indices

Several fit statistics evaluate model fit, analogous to R2 adjustment in multiple regression analysis. Absolute fit indices like the Chi-Square test (Wheaton, 1977), Root Mean Square Error of Approximation (RMSEA) (Browne & Cudeck, 1992), Goodness-of-Fit Index (GFI), and Standardized Root Mean Square Residual (SRMR) (Tanaka & Hubnak, 1985) demonstrate how well the data fits the model. Incremental fit indices, such as Normed-fit index (NFI) (Bollen, 1989), Comparative fit index (CFI) (Bentler, 1990), and Tucker Lewis Index (TLI) (Bentler, 1990; Miles & Shevlin, 2007), compare the chi-square values of the proposed model to a baseline model. Parsimony fit indices like the chi-square/degrees of freedom and Parsimony Goodness-of-Fit Index (PGFI) address model complexity (Mulaik et al., 1989).

4.13 Measurement Model Fit Summary

With the measurement model, individual constructs were assessed. Pooled CFA was evaluated based on nine variables: PE, EE, SI, PEj, BI, AU, VU, and TU. The CFA is based on factor structures without cross-loadings between items. The model was tested using various fit indicators, as recommended by Hu & Bentler (1999). They suggested reporting RMSEA, TLI, and CFI for continuous data, alongside the chi-square value, one absolute fit indicator, and one incremental fit index. Table 4.3 presents key fitness metrics, showing a chi-square value of 513 with 571 degrees of freedom and a p-value of 0.960. The remaining fitness indicators were also close to the acceptable range.

Table 4.3: Fit Indices for Measurement Model

Measure	**Recommended Criteria**	**Measurement Model**	**References**
χ^2 (p-value)	<3	513 (0.906)	(Cho, et.al., 2020)
GFI	>0.8	0.988	(Cho, et.al., 2020)
CFI	>0.9	0.96	(Hu & Bentler, 1999)
RMSEA	<0.06	0.04	(Hu & Bentler, 1999)
Tucker-Lewis Index (TLI)	>0.9	0.946	Bentler and Bonett (1980)
SRMR	<0.10	0.059	(Hu & Bentler, 1999)
RNI	=CFI	0.96	(Goffin, 2010)
Bollen's IFI Value	>0.9	0.987	Bollen, K. A., & Paxton, P. (2000)
Bentler-Bonett Normed Fit Index (NFI)	>0.9	0.984	Byrne, 1994 Schumacker & Lomax, 2004

4.14 Measurement Model of The Constructs

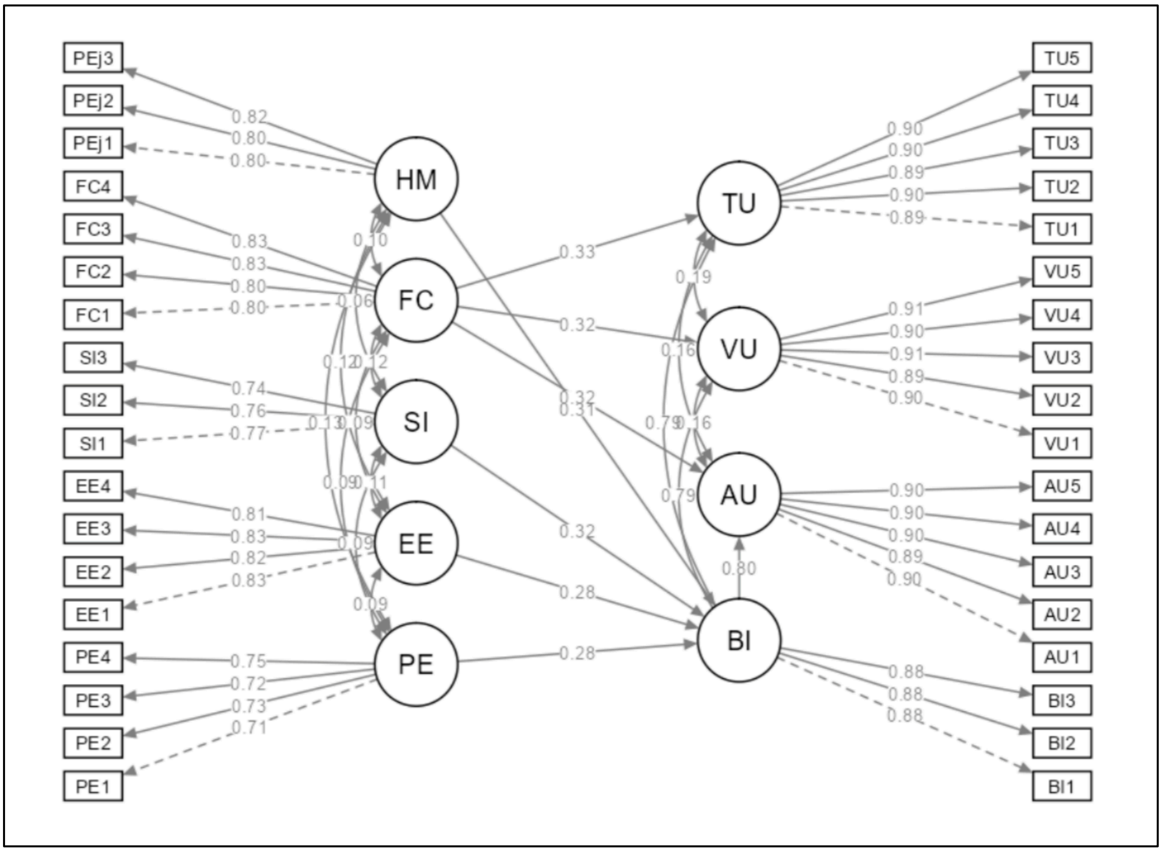

Fig4.1: Path Diagram of the Constructs

A path diagram for a Structural Equation Modeling (SEM) analysis performed on the variables of the current study. SEM is a statistical method used to analyze relationships between multiple variables. Here's a detailed explanation of the path diagram:

4.15 Latent Variables and Measured Variables

The path diagram includes both latent variables and measured variables.

- **Latent variables** are underlying constructs that cannot be directly measured. They are inferred from the measured variables. In this model, the latent variables are:
  - Performance Expectancy (PE)
  - Effort Expectancy (EE)
  - Social Influence (SI)
  - Perceived Enjoyment/Hedonic Motivation (PEj/HM)
  - Facilitating Conditions (FC)
  - Behavior Intention (BI)
  - Amount of ET Use (AU)
  - Variety of ET Use (VU)
  - Type of ET Use (TU)

- **Measured variables** are the specific items used in the survey instrument to measure the latent variables. These are represented by rectangles in the path diagram. For example, PE1, PE2, PE3, and PE4 are likely measured variables that contribute to the latent construct Performance Expectancy (PE) and on similar basis other latent construct has been assed based upon the observed indicators specified the Figure 4.1.

4.16 Relationships between Variables

The arrows in the path diagram represent the relationships between the variables. There are two main types of relationships:

- **Structural relationships:** These arrows represent the hypothesized causal effects of one variable on another. For example, the arrow from PE (Performance Expectancy) to BI (Behavior Intention) suggests that a stronger belief that using technology will lead to good outcomes (higher PE) will lead to a stronger intention to use technology (BI).
- **Measurement relationships:** These arrows represent the relationships between the measured variables and their underlying latent variables. For example, the arrow from PE to PE1 indicates that PE1 is a measure of Performance Expectancy (PE). The path coefficient associated with this arrow represents the strength of the relationship between PE1 and PE. A value closer to 1 indicates a stronger relationship.

4.17 Indices

The path diagram also includes several indices. These indices provide information about the fit of the model to the data. Here are some of the common indices:

- **Standardized path coefficients:** These coefficients represent the strength and direction of the relationships between the variables. They are typically reported as numbers between -1 and 1. A positive coefficient indicates a positive relationship, and a negative coefficient indicates a negative relationship. The strength of the relationship is indicated by the absolute value of the coefficient, with values closer to 1 indicating a stronger relationship.
- **T-values:** T-values are used to assess the statistical significance of the path coefficients. A statistically significant path coefficient means that the relationship between the variables is unlikely to be due to chance.
- **R-squared values:** R-squared values represent the proportion of variance in a variable that is explained by the model. They range from 0 to 1, with higher values indicating a better fit of the model.

4.18 Interpretation of the Path Diagram

Based on the path diagram, here are some observations:

- **Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC)** all positively influence Behavior Intention (BI). This means that people are more likely to intend to use technology if they believe it will produce good results (PE), is easy to use (EE), is supported by others (SI), and has the necessary resources available for use (FC).
- **Perceived Enjoyment of using technology (PEj) or Hedonic Motivation (HM) appears to have a positive effect on Behavior Intention (BI).** This suggests that if people find using technology enjoyable (HM), they are more likely to intend to use it (BI) and actually enjoy using it (PEj).
- The **amount of technology used (AU)**, the **variety of technology used (VU)**, and the **type of technology used** are not directly linked to **Behavior Intention (BI)** in the model. However, they could indirectly influence BI by affecting how much users **enjoy using the technology (Perceived Enjoyment - PEj)**. If someone uses different types

of technology often (like tablets, laptops, or smartboards), it might make the experience more enjoyable for them. This increased enjoyment could then lead to a stronger intention to use the technology in the future, even though the amount or variety or type of use itself doesn't directly determine their intention.

4.19 Results of Validity Assessment of the Descriptive Model Constructs

Our objective is to analyze the constructs' validity using SEM module in Jamovi. All nine constructs were permitted to freely correlate, and the factor correlations are displayed in Figure 4.1 of the measurement model. The values over the bidirectional arrows between the latent variables show their correlations, whereas the values over the arrows represent the standard regression weight of the indicators. CR, AVE, and MSV of the constructs were calculated utilizing the correlations and regression weight tables received from the Jamovi output. Table 4.4 contains their values. All the constructs have a Composite Reliability (CR) of at least 0.78. What this means is that there is enough convergence between the items' internal and construct dependability. AVE for all constructs is greater than 0.5. It is crucial to point out that AVE is a more common degree than CR. AVE indices of higher than 0.5 provide sufficient evidences to researcher to conclude that the convergent validity of a specific concept is sufficient (Fornell & Larker, 1981). For all hypotheses, the CR values also exceed the AVE values, demonstrating sufficient convergent validity. For many constructs, the AVE values are higher than the MSV values, suggesting sufficient discriminant validity. This demonstrated that no issues with discriminant validity exist.

Table 4.4: Reliability, Convergent Validity, Composite Reliability and Discriminant Validity

Constructs	CR	AVE	MSV
PE	0.811	0.519	0.513
EE	0.879	0.644	0.594
SI	0.783	0.546	0.452
PEj/HM	0.862	0.677	0.484
FC	0.893	0.677	0.594
BI	0.895	0.745	0.537
AU	0.950	0.774	0.522
VU	0.957	0.801	0.514
TU	0.950	0.775	0.484

4.20 Significance Test of Individual Parameters

After assessing model fit, the relevance of the individual structural paths was evaluated. This depicts the influence of the latent construct on the observed variable, whose statistical significance is determined by examining the critical ratio (CR) and p values derived from the Jamovi output. CR is "an estimate of the item's regression weight divided by its standard error". CR values are interpreted similarly to the Z-test. If the CR is greater than 1.96, this suggests that the path is statistically significant. The non-significant pathways indicate that these items can be removed (Gallagher, et al., 2008). According to Table 4.5, the CR of each measured variable was above the criterion value of 1.96, and all the paths were statistically significant ($p < 0.01$).

Table 4.5: Significance Test for Individual Constructs

Relationship	Estimate	S.E.	C.R.	P	Comment
BI ← PE	0.28	0.0419	8.76	<0.001	Significant
BI ← EE	0.28	0.0312	9.65	<0.001	Significant
BI ← SI	0.32	0.0350	10.44	<0.001	Significant
BI ← PEi	0.312	0.0338	10.21	<0.001	Significant
AU ← FC	0.323	0.0208	16.64	<0.001	Significant
VU ← FC	0.317	0.0216	16.00	<0.001	Significant
TU ← FC	0.332	0.0208	17.09	<0.001	Significant
AU ← BI	0.799	0.0201	38.56	<0.001	Significant
VU ← BI	0.793	0.0207	37.74	<0.001	Significant
TU ← BI	0.794	0.0202	37.98	<0.001	Significant

4.21 Measurement Model Fit Summary

Overall, the measurement model's fit is satisfactory. All model-fitting indices comply to Hu & Bentler (1999) model-fitting criteria. Exploratory research and confirmatory factor analysis assisted in identifying potential antecedents associated with ET usage and adoption. All the constructs demonstrated discriminant and convergent validity.

4.21.1 Structural Model Evaluation and Hypothesis Testing

The structural model defines how exogenous constructs related to the endogenous constructs. It is ubiquitous in the social and behavioral sciences to utilize SEM, a kind of multivariate statistical modelling.

The main attraction of SEM is its capacity to model the relationship between observed indicators and underlying theoretical or latent constructs and the relationship among latent constructs. It is referred to as covariance-based SEM (CB-SEM) because the SEM assumes covariance structure in the interaction between theoretical constructs (Hair, 2010). Using graphical path diagrams to represent structural equation models, makes it easier to see interconnected components. Rather than focusing on the correlation between the constructs, as is done in correlational analysis, the SEM analysis transforms the measurement model into a structural model that shows the dependent connection.

SEM illustrates the relationship between the studied constructs and consequently contributes to the creation of the model. The main advantage of the SEM is the ability to analyze latent variables. Consequently, it aids in evaluating the link between latent or unobserved variables. SEM computes the impact of independent variables (IDVs) on dependent variables (DVs). SEM facilitates the diagrammatic portrayal of the researcher's conceptual model; it illustrates the hypothesized link between variables. With the aid of a diagram, the study's findings are also readily visible (Gallagher, et al., 2008). The arrow in a reflective model point from latent variables to observable variables. This means that the variance in seen variables is attributable to latent variables and not vice versa, as is the case with formative indicators (Edwards & Bagozzi, 2000). Any modification or manipulation of the latent variables will result in a change in the observable variables. Consequently, any change in the latent variables results in a change in the behavior of the indicators.

After evaluating the model and demonstrating dimensionality and validity of all constructs, SEM approach was used to analyze the link between latent constructs. In other words, the structural links between the antecedents and how they explain the change in the dependent variable were investigated. Using our conceptual understanding and literature review in ET research, 10 research hypotheses were formulated and assessed using SEM. To test these assumptions, we described our structural model by defining the relationship between our proposed constructs: PE, EE, SI, PEj, FC, BI, AU, VU and TU and moderating variables: Experience, Age, Gender, and University Type (Central or State). Diagrammatic representation of the relationship among the constructs is shown in Figure 4.1. PE, EE, SI, PEj, and FC are independent factors, whereas BI, AU, VU and TU are dependent variables.

4.22 Model Assessment Theory

Examining the hypotheses that had been stated, data were collected and analyzed using SEM. SEM is essentially a multivariate methodology used to examine causal models; the technique approximates the structural and measurement models associated with a causal model. The models were evaluated through the Jamovi software application. Using the skewness and kurtosis tests, we first assessed the univariate normality of our data to determine its normality. The test findings demonstrated that the absolute skewness and kurtosis values for all variables are often less than 2, indicating that our data are similar to a univariate normal distribution (Kline, 2005). Mardia's coefficient is employed to assess the multivariate normality of our sample. Bollen (1989) proposed that the sample demonstrates multivariate normality if the Mardia's coefficient is less than p (p + 2), where p represents the number of observed variables. This study's Mardia's coefficient was 2208, which was less than 2499, which is the value of p (p + 2) when p = 46. Consequently, the findings in this investigation were multivariately normal. Prior to analyzing the prospective model, an acceptable estimating method must be determined. Typically, three estimate approaches, namely maximum likelihood (ML), generalized least squares (GLS), and weighted least squares (WLS), could be used to evaluate the fitness of a SEM assuming "the proposed model is correctly described and observed variables are multivariate normal" (Olsson et al., 2000). Based on the presumption of multivariate normality, the ML is believed to be the most efficient and objective of these; it is also the most widely used of the SEM applications (Hair et al., 2006). In contrast, the WLS requires a significantly higher sample size than the ML and GLS (N = 1000 and 2000) to function well.

However, in instances involving misspecification, the ML provides more accurate indices of overall fit; compared to GLS, it has less biased parameter values in terms of routes overlapping with the correct model (Olsson et al. 2000). Considering the normality of the data, the sample size, and the characteristics of the evaluation methodologies, we applied the maximum likelihood estimation (MLE) method to the evaluation.

4.23 Assessment of Structural Model Validity

The structural model is examined using Jamovi software. The MLE was utilized for model evaluation, since this method is tolerant to normality breaches and yields robust findings (Hu & Bentler, 1999). The stated structural model is reflecting in nature.

The model was evaluated with SEM. Our proposed model is depicted in Figure 4.1, where BI and AU, VU and TU are dependent variables. The standardized regression coefficients (displayed above the arrows in the structural model) illustrate the relationship between the dependent and independent variables. They represent the amount of change in a dependent variable that results from a change in an independent variable. One standard deviation of variation in a dependent variable corresponds to one unit of change in the dependent variable.

4.24 Structural Model's Fit Summary

The summary of model-fitting indices is presented in Table 4.9. Overall, the fit indices for the suggested model were adequate (χ^2= 513, GFI= 0.988, CFI = 0.96, TLI = 0.946, and RMSEA=0.04). Harman's single-factor test was implemented with the purpose of testing for a possible shared method bias (Podsakoff et al., 2003). Using a single source or the same procedure to evaluate both the dependent and independent variables in a relationship is how the common method of variance is derived (Craighead, Ketchen, Dunn, & Hult, 2011). We determined a bias of 43% based on our calculations, which is less than 50%. Therefore, we cannot identify any evident common approach bias. Therefore, the proposed model was accepted.

4.25 Test of Direct Relationship

The hypotheses were evaluated to determine whether the antecedents had a direct effect on the dependent variable or result. The standard estimates, critical ratios, and associated p-values were examined to determine the strength and significance of the postulated paths. Table 4.5 displays the standardized path estimates together with the Standardized Estimates (SE), CR, and P values.

The 1st hypothesis stated that PE influences educator's BI to use ET. The output of the SEM validated this hypothesis (β = 0.28, CR= 8.76, $p<0.01$), showing that the PE of ET influences its usage and adoption favorably. The research results are backed by findings from prior studies conducted in a variety of circumstances.

The 2nd hypothesis stated that EE influences educator's BI to use ET. The results of the SEM analysis prove this hypothesis (β = 0.28, CR= 9.65, $p<0.01$), demonstrating that the EE of ET does influence its usage and adoption favorably.

The 3rd hypothesis stated that SI influences educator's BI to use ET. The results of the SEM analysis supported this hypothesis ($\beta = 0.32$, CR= 10.44, $p<0.01$), demonstrating that the SI has a favorable influence on its usage and adoption.

The 4th hypothesis claimed that PEj influences educator's BI to use ET. The results of the SEM analysis prove this hypothesis ($\beta = 0.312$, CR= 10.21, $p>0.01$), demonstrating that the PEj does influence its usage and adoption favorably.

The 5th hypothesis said that the FC influences educator's use behavior of ET. The results of the SEM analysis confirmed this hypothesis.

SEM results of Influence of FC on Use behavior (AU)

($\beta = 0.323$, CR= 16.64, $p>0.01$)

SEM results of Influence of FC on Use behavior (VU)

($\beta = 0.317$, CR= 16.00, $p>0.01$)

SEM results of Influence of FC on Use behavior (TU)

($\beta = 0.332$, CR= 17.09, $p>0.01$)

Behavior Intention influences educator's use behavior of ET, according to Hypothesis 6. The findings of the SEM analysis supported this hypothesis.

SEM results of Influence of BI on Use behavior (AU)

($\beta = 0.799$, CR= 38.56, $p>0.01$)

SEM results of Influence of BI on Use behavior (VU)

($\beta = 0.793$, CR= 37.74, $p>0.01$)

SEM results of Influence of BI on Use behavior (TU)

($\beta = 0.794$, CR= 37.98, $p>0.01$)

4.26 Final Descriptive Model with Standardized Regression Estimates

Table 4.6: Summary of Hypothesis Results

Hypothesis	Path	Standardized Estimate (β)	SE	CR	P	Result
H1	PE → BI	0.28	0.0419	8.76	p < 0.01	Significant
H2	EE → BI	0.28	0.0312	9.65	p < 0.01	Significant
H3	SI → BI	0.32	0.035	10.44	p < 0.01	Significant
H4	PEi → BI	0.312	0.0338	10.21	p < 0.01	Significant
H5a	FC → AU	0.323	0.0208	16.64	p < 0.01	Significant
	FC → VU	0.317	0.0216	16.00	p < 0.01	Significant
	FC → TU	0.332	0.0208	17.09	p < 0.01	Significant
H6	BI → AU	0.799	0.0201	38.56	p < 0.01	Significant
	BI → VU	0.793	0.0207	37.74	p < 0.01	Significant
	BI → TU	0.794	0.0202	37.98	p < 0.01	Significant

Significant at 0.05 level

4.27 Moderating Effects

A moderating variable is one that "influences the nature (e.g., amount and/or direction) of an antecedent's effect on a result" (Aguinis et al., 2017).

In statistical terms, moderation occurs when the connection between an independent variable and a dependent variable varies based on the value of the moderator variable (Dawson, 2014). In addition, moderating variables are essential for determining whether two variables have the same relationship across groups.

In general, a moderating model focuses on the "when" or "for whom"; this variable elucidates or influences an outcome variable in a significant way (Frazier et al., 2004).

4.27.1 Moderation Using Multigroup Modeling

The results of a significant number of studies rely on surveys of a single sample. The downside of studies that pool data is that they don't check for statistically significant changes between groups (Chin & Dibbern 2010). Data collected from a particular population may, however, be unreliable (Sarstedt et al. 2016a). Nevertheless, when categorical moderating factors are included in the data, substantially different group-specific route coefficient estimates may be determined rapidly, which accounts for observed heterogeneity (Sarstedt et al., 2011) and reduces the likelihood of misrepresenting the findings (Sarstedt et al. 2009).

Parameter estimates (such as “outer weights, outer loadings, and path coefficients”) for several sets of data may be compared using “multigroup analysis” (MGA) to see whether there are statistically significant differences between the groups (Hair et al. 2014a; Henseler & Chin 2010). Using MGA, scientists may compare two models that stand in for different populations to see whether there are any differences. So, MGA is helpful for finding out how the dataset differs among predetermined categories (e.g., Hair et al. 2014a; Horn & McArdle 1992; Keil et al. 2000).

MGA has been used to learn what sets apart devoted customers from others who aren't as committed (Picon-Berjoyo et al. 2016). Distinctions between subsets might be uncovered by using this kind of analysis, such as the fact that customers with a high loyalty score have less repercussions from switching providers (Picon-Berjoyo et al., 2016). Insight into group differences allows for assessment with greater precision and strategy execution derived from the findings may be adapted to the many groups incorporated in the data. These differences show the fallacy of treating these groups as if they were one solid block (Schlagel & Sarstedt 2016).

In contrast to the traditional tests of moderation, which examine just one structural connection at once, MGA is a useful tool for testing moderation in a wide range of interrelated contexts (Hair et al. 2010, 2011, 2012c). According to Hair et al. (2014a), "...MGA offers a more holistic picture of the influence of the moderator on the results as the emphasis now is not on evaluating the impact on one specific model relationship but on evaluating the impact on all model relationships." Continuous moderators are relatively easy to analyze but still warrant attention. They are often assessed using many items, which increases their predictive capabilities compared to using a single item (Diamantopoulous et al. 2012; Sarstedt et al. 2016b). This is particularly problematic when considering moderation, which is often associated with modest effects (Aguinis et al. 2005). Because of this, it is more challenging to find useful connections because of our lack of foresight. The measurement model construct also shows up twice in the model when moderating factors are included. The construct is both the moderator variable and a part of the interaction term. Conclusions highlight the shortcomings of using a single criterion to evaluate moderation.

4.27.2 Steps Involved in MGA

Two simple stages allow for the comparison of group-specific results, strengthening the rigor of the data analysis and reducing the possibility of erroneous findings.

As a preliminary stage, data groups are created based on the categorical variable of interest, such as gender (Rutherford et al., 2011. Jamovi's "Generate Data Groups" button organizes the data according to a model's needs. Give the new group a name and choose the category variable from your dataset that you want to use. If you have a hypothesis or view that suggests men and women produce different results, then you will want to conduct a gender-specific analysis. Several categorical factors (such as gender and marital status) allow for more granular analyses and, therefore, more distinct outcome subgroups (single female, single male, married females, married males, etc.).

Data groups are created when the variable of interest has been identified. The results may be seen in a tab labelled "data groups." The classifications are shown in accordance with the encoding of the data. Moreover, the total number of records that fall under each category is shown. A more descriptive name for the group may be given to each line item. When data has been split, it is important to make sure that the resultant subgroups are sizable and similar (Becker et al. 2013; Hair et al. 2014a).

Table 4.7: Groups for MGA

Variable	**G-1**	**Observations**	**G-2**	**Observations**	**G-3**	**Observations**	**G-4**	**Observations**
Gender	Male	693	Female	307				
Age	<40	501	>40	499				
Experience	1-5 years	396	5-10 years	299	10-15 years	192	15 + years	113
University Type	Central	128	State	872				

4.27.3 Testing Moderation Using Multigroup Analysis (MGA)

1. Age

Table 4.8: MGA Indices for Moderator – Age

MGA Results for Age					
Educators Aged upto 40 years			**Educators Aged above 40 years**		
Relationship	**β**	**p**	**Relationship**	**β**	**p**
PE->BI	0.27	<0.001	**PE->BI**	0.289	<0.001
EE->BI	0.277	<0.001	**EE->BI**	0.289	<0.001
SI->BI	0.326	<0.001	**SI->BI**	0.316	<0.001
PEj->BI	0.3	<0.001	**PEj->BI**	0.036	Insignificant
FC->AU	0.327	<0.001	**FC->AU**	0.323	<0.001
FC->VU	0.321	<0.001	**FC->VU**	0.313	<0.001
FC->TU	0.334	<0.001	**FC->TU**	0.331	<0.001

Discussion

It can be observed from the results of MGA that in most cases, the moderators do not have significant impact. However, there is a case though where the relationship is observed to be insignificant, implying that the moderator has a bearing on that relationship. Let us explore the relationships one by one where the moderator is **AGE.** We have grouped the ages into two groups, i.e., above 40 and below 40 years of age.

Let us evaluate the relationships from the above results. The table shows the results of a multi-group analysis (MGA) conducted to investigate the moderating effect of age on a model of ET adoption. The analysis compares educators under 40 years old with those 40 years old and over. Here's a breakdown of the findings and managerial implications:

Analysis of Findings

The table displays relationships between variables with β representing the standardized path coefficient and p representing the significance level. Looking at the table, we can see the following:

- **Influence of PE, EE, SI, and PEj on BI:**
  For both age groups, PE, EE, and SI have a positive and significant influence on Behavior Intention (BI) to adopt ET. This suggests that regardless of age, educators who believe using technology will lead to good outcomes (PE), is easy to use (EE), and is encouraged by others (SI), are more likely to intend to use ET. PEj has a significant effect on BI for respondents under the age 40.

However, the effect of PEj on BI is insignificant for respondents having age more than 40.

- **Moderating Effect of Age:**

  The table presents p-values for the multi-group analysis conducted between the two age groups (under 40 and over 40) for the four variables influencing Behavior Intention (BI) — Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Perceived Enjoyment (PEj). The p-values for PE, EE, and SI are statistically significant (all > 0.05) for both set of respondents. This indicates that the effects of PE, EE, and SI, on BI are consistent across both age groups, with no significant differences observed between them. PEj has a significant effect on BI for respondents under the age 40. However, the effect of PEj on BI is insignificant for respondents having age more than 40.

- **FC on AU, VU, and TU:**

  The analysis shows a positive and significant influence of Facilitating Conditions (FC) on Amount of Technology Used (AU) and Variety of Technology Used (VU) and Type of Technology Used, for both age groups.

Managerial Implications

Based on the findings of this multi-group analysis, here are some managerial implications for promoting ET adoption:

- **Focus on core influences for technology adoption:** Regardless of age, educators' decisions to adopt ET seem to be driven by Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI), Interventions and professional development programs should focus on building these core beliefs and attitudes towards ET. However, the findings reveal that the enjoyment component of the use of technology differ among younger and older educators.
- **Provide supportive conditions:** Both younger and older educators benefit from having access to resources and support (Facilitating Conditions) to use technology effectively. This highlights the importance of providing ongoing technical support, training opportunities, and access to necessary hardware and software for all educators.
- **Tailored strategies might not be necessary:** The analysis suggests that age might not be a significant factor when designing strategies to promote educational technology

adoption. This can simplify the development of professional development programs and interventions, as a single, unified approach might be effective for both younger and older educators. However, it is important to note that this might be specific to the context of this study and further research might be needed in different contexts. The generalizability of these findings might be limited to the specific context and sample of educators used in the study. The study focuses on educators' intentions and reported technology use. Actual classroom practice and integration of technology might require further investigation.

Overall, this multi-group analysis provides valuable insights into how age moderates the relationships between various factors influencing ET adoption. The findings suggest that focusing on core beliefs about educational technology and ensuring supportive conditions are important strategies for promoting technology adoption among educators of all ages.

2. Gender

Table 4.9: MGA Indices for Moderator – Gender

MGA Results for Gender					
Male			Female		
Relationship	β	p	Relationship	β	p
PE->BI	0.29	<0.001	PE->BI	0.246	<0.001
EE->BI	0.247	<0.001	EE->BI	0.371	<0.001
SI->BI	0.327	<0.001	SI->BI	0.276	<0.001
PEj->BI	0.305	<0.001	PEj->BI	0.357	<0.001
FC->AU	0.331	<0.001	FC->AU	0.298	<0.001
FC->VU	0.341	<0.001	FC->VU	0.265	<0.001
FC->TU	0.349	<0.001	FC->TU	0.29	<0.001

Discussion

It can be observed from the results of MGA that in most cases, the moderator has insignificant effect on the relationship among PE, EE, SI, PEj, BI, AU, VU and TU. Let us explore the relationships one by one where the moderator is **GENDER.** We have grouped the gender into two groups, i.e., male and female. The table shows the results of a multi-group analysis (MGA) conducted to investigate the moderating effect of gender on a model of ET adoption. The analysis compares male and female educators. Here's a breakdown of the findings and managerial implications based on the β values (standardized path coefficients) and significance levels (p-values) presented in the table:

Influence of PE, EE, SI, and PEj on BI

- **Main Effects:**

  For both genders, all four variables (PE, EE, SI, and PEj) have a positive and significant influence on Behavior Intention (BI) to adopt ET (all β values positive, all p-values < 0.001). This suggests that regardless of gender, educators who believe using technology will lead to good outcomes (PE), is easy to use (EE), is encouraged by others (SI), and is enjoyable (PEj) are more likely to intend to use ET.

- **Moderating Effect of Gender:**

  MGA suggests that the influence of PE, EE, SI, and PEj on BI is not significantly different between males and females. In other words, gender does not seem to moderate the relationship between these core beliefs and educators' intentions to adopt ET.

FC on AU, VU, and TU

- **Facilitating Conditions (FC) on Amount of Technology Use (AU), Variety of Technology Use (VU) and Type of Technology Use:**

  The analysis shows a positive and significant influence of FC on both AU, VU and TU for both genders (all β values positive, all p-values < 0.001). This indicates that both male and female educators with greater access to resources and support for using technology tend to use more technology and a wider variety of technological tools.

Managerial Implications

Based on the findings of this multi-group analysis, here are some managerial implications for promoting educational technology adoption:

- **Focus on core influences:** Regardless of gender, educators' decisions to adopt educational technology seem to be driven by core beliefs like Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Perceived Enjoyment (PEj). Interventions and professional development programs should focus on building these core beliefs and attitudes towards ET for both male and female educators.
- **Provide supportive conditions:** Both male and female educators benefit from having access to resources and support (Facilitating Conditions) to use technology effectively. This highlights the importance of providing ongoing technical support, training opportunities, and access to necessary hardware and software for all educators.

- **Gender-neutral strategies might be appropriate:** The analysis suggests that gender might not be a significant factor when designing strategies to promote educational technology adoption. This can simplify the development of professional development programs and interventions, as a single, unified approach might be effective for both male and female educators. However, it is important to note that this might be specific to the context of this study and further research might be needed in different contexts.

3. Experience

Table: 4.10: MGA Indices for Moderator – Experience

MGA Results for Experience								
	1 - 5 years		5 - 10 years		10 - 15 years		Over 15 years	
Relationship	**β**	**p**	**β**	**p**	**β**	**p**	**β**	**p**
PE->BI	0.316	<0.001	0.194	<0.001	0.165	0.16	0.328	<0.001
EE->BI	0.204	<0.001	0.399	<0.001	0.266	0.005	0.317	<0.001
SI->BI	0.364	<0.001	0.232	<0.001	0.314	0.002	0.318	<0.001
PEj->BI	0.296	<0.001	0.419	<0.001	0.39	<0.001	0.231	<0.001
FC->AU	0.325	<0.001	0.298	<0.001	0.379	<0.001	0.343	<0.001
FC->VU	0.323	<0.001	0.324	<0.001	0.403	<0.001	0.296	<0.001
FC->TU	0.301	<0.001	0.339	<0.001	0.38	<0.001	0.378	<0.001

Discussion

It can be observed from the results of MGA that in most cases, the moderator Experience does not have a significant impact. However, there are cases where the relationships are observed to be insignificant, implying that the moderator has a bearing on those relationships. Let us explore the relationships one by one for the moderator Experience. We have grouped the experience levels into four categories: 1–5 years, 5–10 years, 10–15 years, and over 15 years.

Analysis of Findings

The table shows the results of a multi-group analysis (MGA) conducted to investigate the moderating effect of experience on the model. The analysis compares educators across different experience groups. Here's a breakdown of the findings:

Influence of PE, EE, SI, and PEj on BI

For most experience groups, PE, EE, and SI have a positive and significant influence on Behavioral Intention (BI). This suggests that regardless of experience, individuals who believe using the system will lead to good outcomes (PE), is easy to use (EE), and is encouraged by others (SI) are more likely to intend to use the system. However, the following nuances emerge:

- The relationship between PE and BI is insignificant for respondents with 10–15 years of experience ($p = 0.16$), indicating a moderating effect of experience on this relationship.
- Similarly, the influence of SI on BI is also insignificant for this group ($p = 0.16$), highlighting that social influence might have less relevance for mid-career professionals.
- PEi shows significant effects on BI for all experience groups, with the strongest influence observed in the 5–10 years group ($\beta = 0.419$).

FC on AU, VU, and TU

Facilitating Conditions (FC) positively and significantly influence the Amount of Technology Used (AU), the Variety of Technology Used (VU), and the Type of Technology Used (TU) across all experience groups. This indicates that regardless of experience, access to supportive resources and infrastructure plays a critical role in determining technology usage.

Managerial Implications

Based on the findings of this multi-group analysis, here are some managerial implications for promoting system adoption:

1. **Focus on Core Influences for Technology Adoption:** Regardless of experience, individuals' decisions to adopt the system seem to be driven by Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI). Interventions and professional development programs should focus on building these core beliefs and attitudes towards system adoption. However, the findings reveal that mid-career professionals (10–15 years of experience) might respond differently to these influences, requiring tailored strategies for this group.
2. **Provide Supportive Conditions:** Facilitating Conditions (FC) significantly impact technology use across all experience groups. Organizations should prioritize providing adequate resources, training, and technical support to enhance system adoption and usage.

3. **Consider Experience-Driven Customizations:** The analysis suggests that experience influences certain relationships, such as PE and SI with BI, especially for mid-career professionals. Tailored strategies that address the unique needs and challenges of this group can enhance adoption rates.
4. **Unified Approach for Other Groups:** For individuals with less than 10 years or over 15 years of experience, a single, unified strategy might suffice, given the consistent influence of core constructs.

4. **University Type**

Table 4.11: MGA Indices for Moderator – University Type

MGA Results for University Type					
Central			**State**		
Relationship	**β**	**p**	**Relationship**	**β**	**p**
PE->BI	0.03387	0.756	**PE->BI**	0.29496	<0.001
EE->BI	0.00638	0.957	**EE->BI**	0.28995	<0.001
SI->BI	0.06061	0.608	**SI->BI**	0.33449	<0.001
PEi->BI	0.58749	<0.001	**PEi->BI**	0.30149	<0.001
FC->AU	0.30717	<0.001	**FC->AU**	0.32371	<0.001
FC->VU	0.26705	0.002	**FC->VU**	0.31896	<0.001
FC->TU	0.05794	0.449	**FC->TU**	0.34654	<0.001

Discussion

It can be observed from the results of the Multi-Group Analysis (MGA) that University Type moderates certain relationships within the model, while others remain unaffected. This analysis compares results across Central and State Universities to understand if the type of university influences the relationships between key constructs. If the p-value is less than 0.05, the moderator does not have an impact. Conversely, a p-value greater than 0.05 indicates a moderating effect of University Type.

Analysis of Findings

Influence of PE, EE, SI, and PEi on BI:

- **Performance Expectancy (PE) → Behavioral Intention (BI):**
    - For Central Universities, the relationship is insignificant (p = 0.756), indicating a moderating effect of University Type. This suggests that in Central Universities, the perceived usefulness of the system does not significantly drive Behavioral Intention.

- In contrast, for State Universities, the relationship is significant ($p < 0.001$), highlighting the importance of Performance Expectancy in influencing Behavioral Intention.

- **Effort Expectancy (EE) → Behavioral Intention (BI):**

    - In Central Universities, the relationship is insignificant ($p = 0.957$), indicating the lack of influence of Effort Expectancy on Behavioral Intention in this context.
    - For State Universities, the relationship is significant ($p < 0.001$), suggesting that ease of use is a critical factor for Behavioral Intention in this group.

- **Social Influence (SI) → Behavioral Intention (BI):**

    - For Central Universities, the relationship is insignificant ($p = 0.608$), showing that Social Influence does not significantly impact Behavioral Intention.
    - For State Universities, this relationship is significant ($p < 0.001$), indicating the importance of peer or societal influence in driving Behavioral Intention.

- **Perceived Enjoyment (PEi) → Behavioral Intention (BI):**

    - Both Central ($p < 0.001$) and State ($p < 0.001$) Universities show significant relationships, with a stronger influence observed in Central Universities ($\beta = 0.58749$). This suggests that Perceived Enjoyment consistently drives Behavioral Intention across university types, albeit with varying strengths.

FC on AU, VU, and TU:

- **Facilitating Conditions (FC) → Amount of Use (AU):**
    - Significant for both Central ($p < 0.001$) and State ($p < 0.001$) Universities, indicating that access to resources and support consistently drives the amount of technology use.
- **Facilitating Conditions (FC) → Variety of Use (VU):**
    - For Central Universities, the relationship is significant ($p = 0.002$), although the strength of the effect ($\beta = 0.26705$) is slightly lower than that for State Universities ($p < 0.001$, $\beta = 0.31896$).

- **Facilitating Conditions (FC) → Type of Use (TU):**
    - The relationship is insignificant for Central Universities ($p = 0.449$), suggesting that Facilitating Conditions do not play a critical role in determining the type of technology used in this context.
    - For State Universities, the relationship is significant ($p < 0.001$), indicating that resources and support play a stronger role in determining the types of technology used.

Managerial Implications

1. **Tailored Strategies for University Types:**
    - Efforts to enhance Behavioral Intention should emphasize Performance Expectancy, Effort Expectancy, and Social Influence in State Universities. For Central Universities, these factors may not have the same impact, suggesting the need for alternative approaches to drive Behavioral Intention.
2. **Consistent Role of Perceived Enjoyment:**
    - Across both university types, Perceived Enjoyment significantly influences Behavioral Intention. Efforts to make technology use enjoyable should be emphasized as a universal strategy.
3. **Focus on Facilitating Conditions:**
    - The consistent role of Facilitating Conditions across most relationships highlights the importance of providing robust infrastructure, training, and resources to enhance technology use, particularly in State Universities.
4. **Addressing Central Universities' Specific Needs:**
    - For Central Universities, the lack of significant relationships between Performance Expectancy, Effort Expectancy, Social Influence, and Behavioral Intention suggests the need for interventions that address unique cultural or systemic factors influencing technology adoption.

CHAPTER-5

HYPOTHESIS TESTING

While statistically analyzing the gathered data, the hypotheses were either supported or ruled out as summarized in the Table 5.1 below.

Table 5.1: Summary of all Hypothesis Tested

Hypothesis		**Result**
H1a	PE influences educator's BI to use ET.	**PE -> BI** **(Supported)**
H1b	The influence of PE on BI will be moderated by gender, age, experience and University Type.	**PE -> BI** **<u>Moderated by:</u>** **Age:** Above 40 **(Not Supported)** Below 40 **(Not Supported)** **Gender:** Male **(Not Supported)** Female **(Not Supported)** **Experience:** 1-5 years **(Not Supported)** 5-10 years **(Not Supported)** 10-15 years **(Supported)** 15 years and above **(Not Supported)** **University Type:** Central **(Supported)** State **(Not Supported)**

While PE's direct effect on BI is significant, moderating factors like age and gender do not influence this relationship. Experience plays a role, with 10-15 years of experience showing support. University type matters, with educators in central universities showing a stronger influence compared to state universities.

H2a	EE influences educator's BI to use ET.	**EE -> BI** ***(Supported)***
H2b	The influence of EE on BI is moderated by gender, age, experience and University Type.	**EE -> BI** **<u>Moderated by:</u>** ***Age:*** Above 40 ***(Not Supported)*** Below 40 ***(Not Supported)*** ***Gender:*** Male ***(Not Supported)*** Female ***(Not Supported)*** ***Experience:*** 1-5 years ***(Not Supported)*** 5-10 years ***(Not Supported)*** 10-15 years ***(Supported)*** 15 years and above ***(Not Supported)*** ***University Type:*** Central ***(Not Supported)*** State ***(Supported)***

The table summarizes the results of hypotheses testing related to educators' behavioral intentions (BI) to use educational technology (ET), influenced by effort expectancy (EE). The findings confirm that EE positively affects BI (H2a supported). However, the moderating effects of demographic factors like age, gender, experience, and university type are mixed. Specifically, experience within the 10-15 years range and employment in state universities show a significant moderating effect, while other categories—such as age groups, gender, and other experience levels—do not. This indicates that the influence of EE on BI is context-dependent, varying by educators' experience and institutional type.

H3a	SI influences educator's BI to use ET.	**SI -> BI** **(Supported)**

H3b	The influence of SI on BI will be moderated by gender, age, experience and University Type.	**SI -> BI** **<u>Moderated by:</u>** **Age:** Above 40 **(Not Supported)** Below 40 **(Not Supported)** **Gender:** Male **(Not Supported)** Female **(Not Supported)** **Experience:** 1-5 years **(Not Supported)** 5-10 years **(Not Supported)** 10-15 years **(Not Supported)** 15 years and above **(Not Supported)** **University Type:** Central **(Supported)** State **(Not Supported)**

The table outlines the hypothesis testing results regarding the influence of social influence (SI) on educators' behavioral intentions (BI) to use educational technology (ET). The findings indicate that SI significantly affects BI (H3a supported). However, the moderating effects of demographic factors like age, gender, experience, and university type are generally unsupported. None of the age groups, gender categories, or experience levels showed significant moderation. Interestingly, the university type had mixed results, with central universities showing a significant moderating effect, while state universities did not. This highlights that SI's impact on BI is only significant in specific institutional contexts.

H4a	PEj/HM influences educator’s BI to use ET.	**PEj -> BI** **Supported**

H4b	The influence of PEj/HM on BI is moderated by gender, age, experience and University Type.	**PEj -> BI** **<u>Moderated by:</u>** ***Age:*** Above 40 ***(Supported)*** Below 40 ***(Not Supported)*** ***Gender:*** Male ***(Not Supported)*** Female ***(Not Supported)*** ***Experience:*** 1-5 years ***(Not Supported)*** 5-10 years ***(Not Supported)*** 10-15 years ***(Not Supported)*** 15 years and above ***(Not Supported)*** ***University Type:*** Central ***(Not Supported)*** State ***(Not Supported)***

The table presents results from hypothesis testing about the role of perceived enjoyment (PEj) or hedonic motivation (HM) in influencing educators' behavioral intentions (BI) to use educational technology (ET). The findings show that PEj/HM significantly affects BI (H4a supported). However, the moderating effects of demographic and contextual factors are mixed. Specifically, age plays a partial role: the effect is significant for those above 40 but not for those below 40. Other moderating factors, such as gender, experience, and university type, show no significant influence. This suggests that the impact of PEj/HM on BI is stronger among older educators, while other factors remain inconsequential.

H5a	FC influences educator's use behavior of ET.	**FC -> AU *(Supported)*** **FC -> VU *(Supported)*** **FC -> TU *(Supported)***
H5b	The influence of FC on use behavior is moderated by gender, age, experience and University Type.	**Only Central University Group is supported to be moderating the effect of FC on TU. Rest all moderating effects are not supported**

The table summarizes the results of hypothesis testing on the role of facilitating conditions (FC) in influencing educators' use behavior of educational technology (ET). The findings confirm that FC significantly affects all three types of use behavior: amount of usage (AU), variety of usage (VU), and type of usage (TU) (H5a supported). Regarding moderating factors (H5b), only the central university group significantly moderates the effect of FC on TU. Other moderating effects, including those based on gender, age, experience, and state universities, are not supported. This indicates that FC plays a broad role in driving usage behavior, with specific contextual significance in central universities for targeted usage.

H6	BI influences educator's use behavior of ET.	**BI -> AU** ***(Supported)*** **BI -> VU** ***(Supported)*** **BI -> TU** ***(Supported)***

The table highlights the hypothesis testing results concerning the influence of behavioral intention (BI) on educators' use behavior of educational technology (ET). The findings confirm that BI significantly impacts all three types of use behavior: amount of usage (AU), variety of usage (VU), and type of usage (TU) (H6 supported). This underscores the critical role of educators' intentions in driving different facets of technology adoption and utilization in educational settings.

Researchers discovered that PE, EE, SI, and PEj/HM all affect BI. All the criteria that have been proved to substantially impact the BI are in line with technology acceptance theories (Venkatesh et al., 2012; Venkatesh et al., 2003; Davis et al., 1989; Ajzen et al., 1985).

Similar to how previous studies on technology acceptance found that different technological and cultural contexts generate different sets of factors that influence the acceptance of a given technology (Venkatesh et al., 2012; Gefen et al., 2003), we can deduce that the same factors that have been found to affect people's willingness to use mobile payment systems (Yang, 2012) and mobile internet access (Venkatesh et al., 2012) also affect their willingness to use ET.

CHAPTER-6

FINDINGS AND RECOMMENDATIONS

6.1 Introduction

We embarked on our journey with the following objectives in mind:

1. To investigate the relationship between performance expectancy (PE), perceived enjoyment (PEj), social influence (SI), and effort expectation (EE) of ET and behavior intention (BI)
2. To investigate the relationship between behavior intention (BI) and ET usage.
3. To investigate the relationship between Facilitating Conditions (FC) and ET usage.
4. To examine the moderating influence of University Type and Demographic Variables in the relationship among the antecedents of Behavior Intention (BI), Facilitating Conditions and ET usage.

UTAUT was the preferred framework in which this study is grounded. One additional predictor was introduced to the existing predictors namely Perceived Enjoyment (PEj). The endogenous factor was also introduced in the form of Use Behavior which was further sub divided as Amount of Use, Variety of Use and Type of Use. There was a dilemma whether to introduce the endogenous factor as it is more suited for longitudinal studies whereas the current study is cross-sectional in design. This issue was resolved by introducing experience as a moderator and this solution was figured out through extensive literature review.

6.2 Interpretation of Findings

Let us discuss the findings.

6.2.1 Performance Expectancy

PE is the extent to which an educator believes that using ET will help him or her achieve professional goals manifold fast. The current study concludes that PE is a strong predictor of an educator's behavior intention to adopt ET. A significant relationship was established through empirical analysis with a path coefficient of 0.28 thus reinforcing and supporting our hypothesis. The results of this research show that teachers' exposure to PE is the second most important factor in determining whether they would use ET. Comparable findings were found by researchers looking into the topic of technology acceptance in the context of mobile applications, such as Chopdar et al. (2019), Fong (2017), Tak (2017), Chopdar et al. (2018), and Ing Phang (2019), all of whom concluded that PE is a crucial factor in determining whether people will adopt certain technologies. The results of this work indicate that educators in India feel ET saves them time when performing their day-to-day tasks. Respondents saw ET as favorable because it increases the likelihood of achieving significant goals. Based on robust quantitative and empirical analysis, it is evident that educators have found ET to be a great boost to their performance and productivity at workplace.

6.2.2 Effort Expectancy

EE is quite often referred to the ease with which educators can start using ET in their day-to-day tasks. It is also common and obvious that EE tends to decrease with the increase in experience. The study in hand finds substantial evidence to conclude that there exists a strong and significant impact of EE on the educator's BI to adopt ET with a path coefficient of 0.28. This finding safely supports our hypothesis. In sync with previous technology adoption studies and models (Cheong, 2013; Venkatesh et al., 2012; Davis et al., 1989), this study demonstrates that EE has significant impact on an educator's propensity to use ET in India. According to research done on m-commerce adoption by Tsu Wei et al. (2009), significant relationship exists between the perceived ease of ET usage and the user's inclination to use ET. Moreover, mobile devices are the second most popular ET medium; therefore, it can be concluded that ET features are somewhat easy to understand and utilize for educators in India. Therefore, the degree of ease associated with employing the applications is a significant factor in determining whether an educator in India would use ET.

Smart AI based tools, intuitive interface, drag and drop interfaces in most of the statistical software, clean and austere UI of several writing software have shortened the learning path and now the learning path for most of the software is less steep. This has reduced the effort of adopting any innovation in ET and educators are accepting them with glee.

6.2.3 Social Influence

The importance assigned by an educator to others' opinions regarding the adoption of ET, whom he or she considers important, is SI. Surprisingly when most of the established studies ruled out the relationship between SI and BI, we were convinced from the inception that due to the nature or ET and the competitive spirit among educators which can also be called professional jealousy (in a positive way though), that chances are rife that there would be a significant relationship between SI and BI. Our study revealed that there is a significant impact of SI on BI with a path coefficient of 0.32 and thus our hypothesis finds support. This study demonstrates that SI is a significant factor in influencing the ET user's BI. Similar results were obtained by Chopdar et al. (2018), Yang (2013), Fong (2017), Tak (2017), and Ing Phang (2017). This indicates that responders are susceptible to peer group influence. Family and friend recommendations have a significant influence on educators for ET adoption. These results indicate that consumers are significantly influenced by the opinions, ideas, and recommendations of important individuals (such as family, friends, and colleagues) who feel they should adopt ET.

Now a days educators are tech-savvy and are assumed to be quick at ET adoption. To avoid being branded as laggards in ET adoption by the significant stake holders, educators are open to put their qualms at rest and adopt ET.

6.2.4 Facilitating Conditions

Facilitating conditions can be defined as the extent to which the infrastructure and support system at the disposal of an educator to adopt ET. The quantitative analysis undertaken found significant relationship between FC and Use Behavior (AU, VU and TU). The path coefficient between FC and AU was found to be 0.32, the path coefficient between FC and VU was found to be 0.32 and the path coefficient between FC and TU was found to be 0.33. All these relations have statistically significant relationships. Confirming to the findings of Venkatesh et al. (2012), this study demonstrates that the influence of FC in predicting the user's BI to utilize ET is substantial. However, this result is consistent with the studies conducted by Baptista and Oliveira (2015). This is likely because the younger generation is accustomed to newer technologies and India has been deluged with ET applications in the recent past and the ease of use has encouraged educators adopt ET.

Through qualitative analysis, it was understood that when there is a conducive infrastructure at workplace, such as a fast and stable internet connection, high-end hardware, smart boards, subscription to advanced statistical software, databases and other tools, educators get an opportunity to explore. Collaborative programs such as peer – to – peer learning, strong support team and regular skill upgradations programs, provide conditions which help educators use more ET. For instance, if the educator is aware that he has a strong support that if anything goes wrong with ET in the classroom, he/she has a dedicated team to help, then he/she can become adventurous and explore various ET and more often. Several institutions have adopted BYOD and this has also facilitated the use of

ET in a much better and faster way as the educator is associated with ET round the clock, which also helps him/her to explore innovations.

6.2.5 Perceived Enjoyment/Hedonic Motivation

PEj/HM refers to an educator's perception of pain or pleasure, which encourages or discourages him/her to either adopt ET or shun using ET for the achievement of his/her professional goals. The study found significant relationship between PEj/HM and BI which is also bolstered by the path coefficient value of 0.31. This is certainly helpful in validating our hypothesis. This study demonstrates that PEj/HM is a significant factor in influencing the ET user's BI. This result was remarkably like those of Chopdar et al. (2018), Tak (2017), Ing Phang (2019), and Miladinovic (2019). This study indicates that PEj/HM is also a crucial factor in determining the usage of ET. This demonstrates that educators enjoy employing ET applications owing to its features and functionality. This indicates that educators are driven by the enjoyment of ET and their engagement in the activity.

Digging deeper it is understood that this relationship is obvious. Most of the novel ET innovations are gamified and this is at times addictive as well. Moreover, some educators have also expressed that when they see their machine doing amazing things with great ease, they simply cannot resist using more of it. Besides, they also feel that when they use different technologies such as collaborative tools, they can engage with their students in a better way. All these aspects have encouraged the educators use more of ET, explore variety of tools, and use ET for multiple purposes.

6.2.6 Behavior Intention

An educator's perceived likelihood that he/she will engage with ET can be defined as BI on this study. BI in this study is a predictor to AU, VU and TU. All the three relations were found to be significant. The path coefficient between BI and AU is 0.80, between BI and VU is 0.79 and between BI and TU is 0.79. This is a very strong relationship and the explanation to such relationship is equally fascinating.

Educators mentioned that after the launch of Jio, they started to experience faster and more stable internet connectivity. This encouraged them to use videos in their pedagogy. They were also capable of downloading several programs and apps in a few minutes which earlier took some days to download. This access to cheap and fast internet made them adventurous and they started exploring ET and tried to innovate technologies to include them in their pedagogy. Further interactions with Gen Z also made them hip. They want to walk the talk of the new generation. This phenomenon also was instrumental in their behavioral transformation.

Further Covid 19 fuelled the usage of ET to a great extent. Remote classes or online classes were very taxing from the educators' point of view. They felt drained as they delivered the lectures online because it was becoming more and more challenging to engage students online. They needed a hook. ET was the ultimate respite. This was when many of the educators started experimenting with ET. They flipped their classrooms, introduced innovative pedagogy, and started experimenting with collaborative tools. During this time many educators also mentioned that they upgraded their computers and many of them even bought new machines. To their surprise, the machines available in the market were also faster and more powerful. This also curbed their lethargy and resistance towards ET. Several educators have also reported that during the Covid lockdown, many of them even started their blogs and YouTube channels.

6.2.7 Role of Moderators

A moderating variable in one that "influences the nature (e.g. amount and/or direction) of an antecedent's effect on a result. To state differently a moderating model focuses on "when" or for "whom", a moderating variable elucidates or influences an outcome variable in a significant way. The moderators used in the study were derived mainly from the original UTAUT, which included age, gender, and experience. This study also added a new moderator which was thought to have significant impact on the relationships between the antecedents and BI and that moderator is University type. This study focused mainly on Central Universities and State Universities only. Multi Group Analysis was used to evaluate the moderation effect. MGA is a powerful tool for investigations which demonstrate observed heterogeneity.

Firstly, let us discuss the moderating effect of age on the relationships. The proposed framework postulated the relationship between the antecedents and BI, we test the moderating effect of age on this relationship. Most of the relationships were statistically significant when moderated by age, but there were a few instances where the moderating effect was statistically insignificant. Two groups were created as per extant literature, and they were above 40 years of age and below 40 years of age.

Not surprisingly though the relationship between PEj/HM and BI when moderated by age for the group of 40 years and above, the relationship was not found to be significant. There could be several explanations for the same. One of it could be that age makes educators more resistant to change. Several older respondents in our study mentioned that all these gadgets and gizmos are child's play and actual teaching can never be delivered through ET. It requires the maturity and subject acumen which only an educator can deliver. One of the strongest statements that was recorded that those who cannot teach, use all these fancy gizmos. So, unless there was a strong tangible benefit associated with the use of ET, older educators resist or do not demonstrate any intention to adopt ET just for the sake of enjoyment.

The second moderator tested was gender. In case of both the genders, all the relationships when moderated with gender were found to be significant. This implies that the relationship between PE and BI, EE and BI, PEJ and BI, SI and BI, when moderated with gender has significant relationship and it is immaterial that the educator is either male or female, the propensity to influence BI is significant in both the cases.

The third moderator which was tested was experience. Based on experience, four groups of educators were created, and this was strongly supported by literature. Those groups were of educators with 1 – 5 years of experience, 5 – 10 years of experience, 10 – 15 years of experience and educators with 15 or more years of experience. All the relations tested namely relationship between PE and BI, EE and BI, SI and BI, PEj and BI, BI and AU, BI and VU, BI and TU, showed significant relationship when moderated with experience. There were a few borderline cases though such as the relationship between EE and BI for the group with experience of 10 -15 years of experience, where the P – Value was exactly 0.005. Now giving a benefit of doubt, we have accepted the hypothesis, but this is very close to the extant literature, where it can be found that as experience increases, the effort expectancy become irrelevant.

The fourth moderator which was tested was University Type. For this moderator, two groups were created. One group was that of educators from Central Universities and the second group was that of educators from State Universities. Surprisingly all the relationships when moderated with State Universities demonstrated significant relationships, whereas several relationships in the case of the group of educators from Central Universities did not show significant relationships.

The prominent ones where the relationships were not significant are the relationship between PE and BI, EE and BI, SI and BI, and FC and TU. From the analysis in this study, it has been observed that university type has an interesting impact on the BI to adopt ET. From the study it could be observed that the direct antecedents such as PE, EE and SI did not have any significant relationship when moderated by university type (Central

University), whereas PEj has significant relationship with BI when moderated by university type. Contrary to this all the direct antecedents, i.e., PE, EE, SI and PEj had significant relationship with BI to adopt ET when moderated by university type (State University).

Literature reveals that educators in State Universities are resource hungry (Setiasih et al., n.d.-b). They do not have access to the world class facilities that the educators in Central Universities have. In this context, the educators in State Universities gobble up all the opportunities that come their way. They use frugal technologies such as social media or web conferencing technologies to reach out to their students or for their Online Reputation Management. They are always on the lookout for various technologies which can improve their productivity by reducing their effort and at the same time their visibility is enhanced.

Another argument that was also tabled that several Central Universities are in their infancy or are newly formed. 37 out of 56 Central Universities are formed after 2000. In this context, there are several structural changes happening and this could be one reason why the educators are more engaged in administrative tasks or are at the cusp of transition as several educators are newly recruited.

One behavioral aspect that was underscored that the state universities are more ambitious and want to attain higher status and wish to attain the status of central universities. In this context, the educators are either encouraged or coerced to adopt high levels of innovation. Probably this also results in higher degree of adoption of ET in state universities. The significant relationship between PEj and BI when moderated by university type (Central University), is very interesting to note. That is to say that those educators who enjoyed using ET or ET use was a source of enjoyment for them, showed higher proclivity to adopt ET.

6.3 Implications of the Study

ET has shown its prowess during the Covid Lockdown and almost everyone has got a taste of it. Educators either willingly or reluctantly started using ET and this has resulted in the boom in this sector. Several new start-ups are emerging in this domain and is also becoming a big employer. Schools, colleges and universities have understood the importance of going digital and have also understood the myriad benefits that this innovation ushers.

6.3.1. Implications for Management Practioners

The findings of this study offer valuable managerial implications for **Educational Technology (ET)** companies by connecting them to the key constructs of **Performance Expectancy (PE)**, **Effort Expectancy (EE)**, **Social Influence (SI)**, **Behavior Intention (BI)**, and **Perceived Enjoyment (PEj)**.

1. **User Interface (UI) Design and Effort Expectancy (EE):**

   The **user interface (UI)** of ET products must be simple, intuitive, and easy to navigate. A well-designed UI reduces the **effort expectancy (EE)**, as educators will find the technology easier to use. For instance, minimizing unnecessary steps and simplifying processes like content creation or collaboration can reduce the perceived complexity. This can significantly increase educators' intention to use ET products (BI) as ease of use is a critical factor for adoption.

2. **Building Strong Educator Communities and Social Influence (SI):** ET companies need to shift their focus towards educators by fostering **strong and vibrant communities** of teachers. While current marketing efforts tend to target students, educators are key opinion leaders who can influence technology adoption through **recommendations, referrals, and endorsements**. Building educator-centric communities will amplify **social influence (SI)**, which directly impacts **behavior intention (BI)**, leading to more consistent and sustained adoption of ET products. Such communities can also serve as platforms for knowledge sharing and product feedback, strengthening educators' trust in the products.

3. **Performance Expectancy (PE) and Effective Promotions:**

   ET companies often emphasize product features when promoting their products. However, promotional strategies should focus on showcasing how ET products help educators achieve **specific goals and desired outcomes**. Highlighting practical benefits and **performance improvements** will enhance **performance expectancy (PE)**, ultimately strengthening educators' **behavior intention (BI)** to adopt the technology. Packaging, both physical and digital, should also be taken seriously, as it plays a subtle yet important role in conveying professionalism and reliability.

4. **Leveraging Educators as Influencers to Enhance Social Influence (SI):** Many educators are active as **YouTubers, bloggers, and content creators**, with significant followings among peers and students. Collaborating with such educators to create promotional materials or content can help ET companies enhance their reach and credibility. These educators act as influencers, increasing the **social influence (SI)**, which positively affects behavior intention (BI) to adopt ET products. This strategy taps into trusted sources within the educator community, making ET solutions more relatable and appealing.

5. **Use Cases, Perceived Enjoyment (PEj), and Technology Usage:**

   Educators often utilize only a limited set of features from ET products. ET companies must identify the most **common use case scenarios** and develop clear case studies that demonstrate how their products enhance educators' **perceived enjoyment (PEj)** and productivity. Additionally, creating video tutorials and **help content** for these scenarios will reduce initial adoption barriers (EE) and improve educators' behavior intention (BI). Handy instructional content will also encourage greater **amount, variety, and type** of technology use, leading to extended usage patterns.

6. **Pricing Strategies and Age-Specific Preferences:**

   The study found age-related differences in pricing preferences. Educators **40 years and older** tend to prefer **lifetime licenses** over subscription models, as they value stability and long-term utility. In contrast, **younger educators** prefer **short-term subscriptions**, which allow them to explore multiple technologies without being tied to a single product. ET companies should design **flexible pricing strategies** that cater to these preferences, such as offering both lifetime licenses and subscription options. Tailoring pricing structures will ensure broader acceptance and adoption of ET products across different age groups.

By addressing these managerial implications, ET companies can create educator-friendly products that enhance ease of use (EE), build strong social influence (SI), improve perceived performance (PE), and boost overall enjoyment (PEj). These efforts will positively influence educators' **behavior intention (BI)**, leading to increased adoption, sustained use, and greater satisfaction with ET products.

6.3.2. Implications for Academicians and Researchers

This study provides significant insights for academicians and researchers, particularly in the domains of Education Technology (ET), behavioral science, and higher education management. By exploring the determinants of user acceptance, behavior intention, and actual usage of ET among educators, the study contributes to the growing discourse on digital transformation in academia. Below are the key implications for academicians and researchers:

1. Enriching the Understanding of ET Adoption in Higher Education

- The study highlights the pivotal role of **Performance Expectancy (PE)** and **Effort Expectancy (EE)** as critical predictors of ET adoption. Academicians can leverage these findings to design interventions aimed at improving educators' perceptions of ET's utility and ease of use.
- Researchers can build upon the theoretical framework by incorporating additional constructs, such as **hedonic motivation**, **self-efficacy**, and **technology anxiety**, to capture a more comprehensive view of ET adoption in varied academic contexts.

2. Expanding the UTAUT Framework

- By introducing novel dimensions like **Amount of ET Use**, **Variety of ET Use**, and **Type of ET Use**, the study extends the UTAUT framework to include post-adoption behavior. This extension provides a foundation for future studies to explore the depth and breadth of ET usage in education and other domains.

- Researchers can adapt and validate these constructs in different geographical, cultural, and institutional settings, enriching the global understanding of technology acceptance and use behavior.

3. Addressing Institutional Disparities

- The study reveals significant differences in ET adoption between Central and State Universities, highlighting disparities in infrastructure, training, and support systems. For researchers, this opens avenues to study the impact of institutional resources on ET adoption and propose policy recommendations to bridge these gaps.
- Academicians can collaborate with policymakers to advocate for equitable resource allocation, ensuring that under-resourced institutions have access to the tools and support necessary for effective ET integration.

4. Informing Pedagogical Practices

- The findings emphasize that educators utilize ET for diverse purposes, including **teaching**, **research collaboration**, and **administrative efficiency**. This provides a roadmap for academicians to develop training programs that align ET tools with specific pedagogical objectives.
- Researchers can explore the interplay between ET adoption and teaching methodologies, assessing how technology-driven approaches impact student engagement, learning outcomes, and faculty satisfaction.

5. Encouraging Multidisciplinary Research

- By linking behavioral theories with practical applications in education, this study underscores the importance of multidisciplinary research. Academicians from fields such as psychology, management, and information systems can collaborate to further investigate the psychological, organizational, and technological factors influencing ET adoption.
- Researchers can also explore cross-disciplinary applications of the UTAUT framework, extending its relevance beyond education to domains such as healthcare, corporate training, and public administration.

6. Promoting Longitudinal and Comparative Studies

- The study provides a snapshot of ET adoption in Indian higher education. Researchers can conduct longitudinal studies to examine how ET usage evolves over time, particularly in response to technological advancements, policy changes, and cultural shifts.
- Comparative studies across countries, regions, or institutional types can shed light on the universal and context-specific factors influencing ET adoption, offering valuable insights for global academic communities.

7. Developing Customized Solutions

- The study highlights the importance of tailoring ET solutions to educators' specific needs and institutional goals. Academicians can collaborate with developers and industry stakeholders to design user-centric technologies that address educators' pain points and enhance their teaching and administrative efficiency.
- Researchers can delve deeper into the design and usability of ET platforms, assessing how factors such as user interface, accessibility, and functionality influence adoption and sustained usage.

8. Shaping Future Research Agendas

- The findings lay the groundwork for future research on critical themes such as **technology acceptance in resource-constrained environments**, **the role of peer influence in technology adoption**, and **the impact of demographic factors on ET usage behavior**.
- Academicians can integrate these themes into their research agendas, fostering a deeper understanding of the complex dynamics shaping digital transformation in education.

9. Advancing the Policy and Practice Interface

- By providing actionable insights into the barriers and enablers of ET adoption, the study bridges the gap between academic research and policy implementation. Researchers can use this knowledge to engage with policymakers and institutional leaders, advocating for evidence-based strategies to promote ET integration.

- Academicians can play a critical role in translating research findings into practical guidelines for educators, ensuring that ET adoption is both effective and sustainable.

6.3.3. Implications for Society and Community

This study has far-reaching implications for society and the broader community, particularly in the context of digital transformation in education. By exploring the factors influencing educators' adoption and utilization of Education Technology (ET), the research provides valuable insights into how technology can address social challenges, promote equitable access to education, and empower communities. Below are the key societal and community-level implications:

1. Enhancing Educational Equity

- The findings highlight disparities in ET adoption across Central and State Universities, emphasizing the need for equitable distribution of resources. Addressing these gaps can significantly improve access to quality education for underserved communities, particularly in rural and remote areas.
- Society benefits when educators in resource-constrained settings are equipped with ET tools that enable inclusive education, allowing students from diverse socio-economic backgrounds to participate in and benefit from modern learning practices.

2. Bridging the Digital Divide

- The study underscores the role of facilitating conditions, such as infrastructure and technical support, in driving ET adoption. Investments in digital infrastructure, such as high-speed internet, e-learning platforms, and affordable devices, can help bridge the digital divide within and between communities.
- Community-level initiatives, such as technology literacy programs and local training workshops, can empower educators and students to embrace digital tools, fostering a culture of lifelong learning.

3. Promoting Lifelong Learning and Skill Development

- ET adoption enables educators to deliver personalized, skill-oriented, and interactive learning experiences, which can prepare students for the demands of the 21st-century workforce. This, in turn, enhances the employability and productivity of individuals, contributing to economic growth and social mobility.

- Community education programs leveraging ET can support reskilling and upskilling efforts for adults, enabling them to adapt to changing job markets and technological advancements.

4. Strengthening Social Cohesion through Education

- Technology-driven education fosters collaboration, interaction, and knowledge-sharing among diverse groups of students and educators. This can promote understanding, tolerance, and cohesion within communities by breaking down barriers related to geography, language, and socio-economic status.
- Online platforms and virtual classrooms can connect learners and educators from different cultural and regional backgrounds, fostering a sense of global community and mutual respect.

5. Supporting Educational Resilience

- The COVID-19 pandemic demonstrated the critical role of ET in maintaining continuity of education during crises. By equipping educators with the skills and tools to integrate ET into their teaching practices, society can build resilience against future disruptions, ensuring that learning remains uninterrupted.
- Communities with access to robust ET ecosystems are better prepared to adapt to emergencies, from natural disasters to economic downturns, safeguarding the educational rights of vulnerable populations.

6. Empowering Educators as Community Leaders

- The study emphasizes the importance of educators' behavioral intention and actual usage of ET in driving its societal impact. Educators who effectively use ET become role models and community leaders, inspiring others to adopt and adapt to technological advancements.
- By integrating ET into teaching, research, and administrative tasks, educators contribute to creating a knowledge-driven society where innovation and technology are embraced as tools for social progress.

7. Facilitating Social and Economic Development

- The widespread adoption of ET has the potential to transform communities by fostering educated, skilled, and informed citizens. This creates a positive cycle of social and economic development, where access to quality education leads to higher incomes, reduced inequality, and improved standards of living.
- The study's findings highlight the role of ET in streamlining educational administration and improving institutional efficiency, indirectly benefiting society by optimizing the use of public funds and resources.

8. Empowering Marginalized Groups

- ET can play a pivotal role in empowering marginalized groups, such as women, economically disadvantaged individuals, and persons with disabilities, by providing them with flexible, accessible, and affordable learning opportunities.
- The study's emphasis on training and capacity building for educators can help ensure that these technologies are utilized effectively to address the unique challenges faced by these groups, fostering greater inclusivity and representation.

9. Driving Innovation in Community Education

- The study underscores the diverse applications of ET, from virtual learning environments to gamification tools, which can be extended to community education programs. Libraries, community centers, and non-profit organizations can adopt these technologies to offer free or low-cost educational resources to underserved populations.
- Innovation in ET can also support initiatives such as adult literacy programs, vocational training, and health education campaigns, creating a ripple effect of positive change within communities.

10. Creating Awareness and Advocacy for Technology in Education

- The study highlights the importance of social influence in shaping ET adoption. Communities and local organizations can play a proactive role in advocating for technology's benefits in education, encouraging stakeholders to invest in and support digital learning initiatives.

- Public awareness campaigns and community forums can help demystify ET, addressing misconceptions and resistance while showcasing success stories that inspire wider adoption.

6.3.4. Implications for Policy Makers

The findings of this study provide critical insights for policymakers tasked with shaping the future of education in the digital era. By exploring the determinants of Education Technology (ET) adoption and usage behavior among educators, the research identifies areas where policy interventions can maximize the potential of ET to enhance teaching, learning, and institutional performance. Below are the detailed implications for policymakers:

1. Promoting Equitable Access to Technology

- The study highlights significant disparities in ET adoption between Central and State Universities, primarily due to unequal access to infrastructure, resources, and technical support. Policymakers must prioritize bridging this digital divide by allocating resources to underfunded institutions, especially in rural and remote areas.
- Policies should promote nationwide implementation of affordable high-speed internet, subsidized digital devices, and infrastructure grants to ensure all educators and students have equal opportunities to leverage ET.

2. Encouraging Investment in Digital Infrastructure

- The study underscores the importance of **Facilitating Conditions (FC)**, such as infrastructure and institutional support, in translating behavioral intention into actual ET use. Policymakers can incentivize investments in technology infrastructure, including Learning Management Systems (LMS), Virtual Learning Environments (VLEs), and smart classrooms.
- Creating partnerships between public and private sectors can accelerate the development and deployment of cutting-edge ET solutions, ensuring scalability and sustainability.

3. Designing Targeted Training and Capacity-Building Programs

- The findings reveal that **Effort Expectancy (EE)** is a significant barrier for educators, particularly in institutions with limited exposure to ET. Policymakers should mandate the development of nationwide training programs to improve educators' digital literacy and confidence in using ET tools.
- Tailored training modules that address the specific needs of educators at various stages of their careers can enhance the effectiveness of these programs. Additionally, policymakers can establish certification programs to incentivize educators to participate in continuous professional development.

4. Developing Comprehensive ET Adoption Frameworks

- Policymakers should create standardized frameworks for ET adoption, grounded in empirical findings such as those presented in this study. These frameworks should address the entire lifecycle of ET integration, from initial training and resource allocation to ongoing support and evaluation.
- The inclusion of performance benchmarks and measurable outcomes can help institutions assess the impact of ET adoption and identify areas for improvement.

5. Addressing Institutional and Demographic Disparities

- The study highlights the moderating effects of institutional type and demographic factors on ET adoption. Policymakers must design inclusive policies that cater to the diverse needs of educators based on their age, gender, years of experience, and institutional affiliation.
- For example, initiatives that focus on empowering female educators, younger faculty, or educators in rural institutions can foster a more inclusive approach to technology integration in higher education.

6. Enhancing Policy Alignment with National Education Goals

- The study's findings align with the goals of policies such as India's **National Education Policy (NEP) 2020**, which emphasizes digital transformation and technology-driven education. Policymakers can leverage these insights to refine existing policies and ensure alignment with broader national objectives.

- Policies should explicitly include provisions for integrating ET into curricula, teacher training programs, and administrative processes, ensuring that technology adoption supports institutional and national development goals.

7. Strengthening Monitoring and Evaluation Mechanisms

- To ensure the effectiveness of ET policies, policymakers need robust monitoring and evaluation mechanisms. This study highlights the importance of measuring behavioral intention and actual usage to assess the impact of ET initiatives.
- Policymakers can implement data-driven approaches to track ET adoption rates, identify challenges, and evaluate the outcomes of interventions. Regular audits and feedback loops can ensure continuous improvement in policy implementation.

8. Encouraging Collaborative Policymaking

- The study underscores the role of **Social Influence (SI)** in shaping educators' attitudes toward ET adoption. Policymakers can foster collaboration among stakeholders, including educators, institutional leaders, technology providers, and community representatives, to create policies that reflect diverse perspectives and needs.
- Engaging educators in the policymaking process can ensure that policies are practical, relevant, and widely accepted.

9. Incentivizing Innovation in Education Technology

- To encourage the development of innovative ET solutions, policymakers can establish funding schemes, grants, and competitions for startups and research institutions. Supporting indigenous technology development can reduce dependency on foreign solutions and create a self-sustaining ET ecosystem.
- Policies that reward innovation and recognize institutions or educators who demonstrate exemplary ET integration can drive wider adoption and inspire others to follow suit.

10. Preparing for Crisis-Resilient Education Systems

- The COVID-19 pandemic demonstrated the need for resilient education systems capable of adapting to disruptions. Policymakers can use the findings of this study to design contingency plans that leverage ET for uninterrupted learning during emergencies.

- Investments in scalable ET platforms, virtual training for educators, and backup infrastructure can ensure that education systems remain functional in the face of future crises.

11. Reducing Resistance to Change through Awareness Campaigns

- Resistance to ET adoption often stems from a lack of awareness about its benefits. Policymakers can initiate public awareness campaigns highlighting success stories and demonstrating the positive impact of ET on education quality and accessibility.
- Such campaigns can address common misconceptions, foster community support for ET initiatives, and encourage educators to embrace digital transformation.

12. Promoting Global Competitiveness in Education

- By driving widespread ET adoption, policymakers can position India as a global leader in education technology. The findings of this study provide a roadmap for creating competitive, technology-driven education systems that attract international students and collaborations.
- Aligning ET policies with global trends and standards can enhance the reputation and influence of Indian higher education institutions on the international stage.

6.4 Limitations and Scope for Further Study

Coming to the limitations, one striking limitation of this study is that had it been a longitudinal study rather than cross sectional one, the post adoption behavior or the understanding about the use behavior could have been deeper and richer. Usage amount, type and variety of any technology evolves over time and the inherent resistance towards any technology can evaporate when it is used for a prolonged period of time. On the contrary when an issue with the User Interface (UI) of the technology creates a poor User Experience (UX), the initial enthusiasm to use a certain technology could wane over time. So if an opportunity arises, there is certainly a need to carry forward this study with a longitudinal design.

Most of the data collection part happened during the Covid lockdown. This did not provide us with the opportunity to meet the respondents face to face. Had there been an opportunity to meet the respondents, their anecdotes, insights and observations which they could have shared would have made this study more meaty.

Further, we could not include the Private Universities in our study and a majority of the Private Universities did not have the details of their educators on their websites. This was a serious limitation. Including educators from the Private Universities also could have made this study more complete and could also have added richer and deeper dimensions to the study. There was a temptation to include a few educators from Private Universities, who could be approached conveniently, but that would have made our sampling non probabilistic, which we did not want to do. There could be independent studies undertaken in the future with a focus on Private Universities.

The study in question has not taken voluntariness into consideration as a moderating variable in accordance to the way it was used in the UTAUT model. The study worked under the assumption that all the educators are using or abstaining from ET voluntarily and there was no mandate to make use of ET. There was no deliberate effort to check this assumption. In recent times certain ET has been made mandatory to use in most of the universities in India, so it would be really interesting to observe the moderating effect of voluntariness on the overall model.

Finally, the emphasis of this study was to examine the BI and Use behavior of ET, that is to say that whether intent existed and how much the educators use ET, the types or variety of ET they use, but the study did not test the dexterity and prowess with which the educators make use of ET. There was no effort made to even test the deliverables produced by the educators with the help of ET. If the efficacy and dexterity with which educators are using ET and the tangible or intangible deliverables that they are able to produce with the help of ET is tested, we are sure that it would produce interesting insights.

Though Artificial Intelligence (AI) has taken unprecedented importance in the realms of Education, yet this study does not pay much heed to it.

References

Abdullah, H., Sahudin, Z., Bahrudin, N. Z., Bujang, I., & Khalid, K. (2023). Determinants of Educational Technology Acceptance: An Integration of TAM and UTAUT. *Asian Journal of University Education*, *19*(4), 638–650. https://doi.org/10.24191/ajue.v19i4.24626

Abramo, G., & D'Angelo, C. A. (2015). The relationship between the number of authors of a publication, its citations and the impact factor of the publishing journal: Evidence from Italy. *Journal of Informetrics*, *9*(4), 746-761.

Adams, C. A., & Larrinaga-González, C. (2007). Engaging with organisations in pursuit of improved sustainability accounting and performance. *Accounting, Auditing & Accountability Journal*, *20*(3), 333-355.

Adams, D. A., Nelson, R. R., & Todd, P. A. (1992). Perceived usefulness, ease of use, and usage of information technology: A replication. *MIS quarterly*, 227-247.

Adams, M. J. (1998). The three-cueing system.

Adiguzel, T., Kaya, M. H., & Cansu, F. K. (2023). Revolutionizing education with AI:Exploring the transformative potential of ChatGPT. *Contemporary Educational Technology*, *15*(3), ep429. https://doi.org/10.30935/cedtech/13152

AECT (1977). The Definition of Educational Technology, Washington: AECT.

Agarwal, R., & Prasad, J. (1997). The role of innovation characteristics and perceived voluntariness in the acceptance of information technologies. *Decision sciences*, *28*(3), 557-582.

Agarwal, R., & Prasad, J. (1998). A conceptual and operational definition of personal innovativeness in the domain of information technology. *Information systems research*, *9*(2), 204-215.

Agarwal, R., & Prasad, J. (1998). The antecedents and consequents of user perceptions in information technology adoption. *Decision support systems*, *22*(1), 15-29.

Aguinis, H., Beaty, J. C., Boik, R. J., & Pierce, C. A. (2005). Effect size and power in assessing moderating effects of categorical variables using multiple regression: a 30-year review. *Journal of applied psychology*, *90*(1), 94.

Aguinis, H., Edwards, J. R., & Bradley, K. J. (2017). Improving our understanding of moderation and mediation in strategic management research. *Organizational research methods*, *20*(4), 665-685.

Ajzen, I. (1985). From intentions to actions: A theory of planned behavior. In *Action control: From cognition to behavior* (pp. 11-39). Berlin, Heidelberg: Springer Berlin Heidelberg.

Gollwitzer, P. M., & Bargh, J. A. (Eds.). (1996). *The psychology of action: Linking cognition and motivation to behavior*. Guilford Press.

Ajzen, I. (1991). The Theory of planned behavior. *Organizational Behavior and Human Decision Processes*.

Ajzen, I., & Fishbein, M. (1975). A Bayesian analysis of attribution processes. *Psychological bulletin*, *82*(2), 261.

Ajzen, I., & Fishbein, M. (2004). Questions raised by a reasoned action approach: comment on Ogden (2003).

Aksnes, D. W., Langfeldt, L., & Wouters, P. (2019). Citations, citation indicators, and research quality: An overview of basic concepts and theories. *Sage Open*, *9*(1), 2158244019829575.

Alalwan, A. A. (2020). Mobile food ordering apps: An empirical study of the factors affecting customer e-satisfaction and continued intention to reuse. *International Journal of Information Management*, *50*, 28-44.

Alharbe, N. R. (2019). Improving usable-security of web based healthcare management system through fuzzy AHP. *International Journal of Advanced Computer Science and Applications*, *10*(8).

Alam, M. Z., Hoque, M. R., Hu, W., & Barua, Z. (2020). Factors influencing the adoption of mHealth services in a developing country: A patient-centric study. *International journal of information management*, *50*, 128-143.

Alapetite, A., Andersen, H. B., & Hertzum, M. (2009). Acceptance of speech recognition by physicians: A survey of expectations, experiences, and social influence. *International journal of human-computer studies*, *67*(1), 36-49.

Al-Emran, M., Mezhuyev, V., & Kamaludin, A. (2018). Technology Acceptance Model in M-learning context: A systematic review. *Computers & Education*, *125*, 389-412.

Almaiah, M. A., Alamri, M. M., & Al-Rahmi, W. (2019). Applying the UTAUT model to explain the students' acceptance of mobile learning system in higher education. Ieee Access, 7, 174673-174686.

Almaiah, M. A., Alamri, M. M., & Al-Rahmi, W. (2019). Applying the UTAUT model to explain the students' acceptance of mobile learning system in higher education. *Ieee Access*, *7*, 174673-174686.

Alwin, D. F. (1992). Information transmission in the survey interview: Number of response categories and the reliability of attitude measurement. *Sociological methodology*, 83-118.

Ameen, N., & Willis, R. (2018). An analysis of the moderating effect of age on smartphone adoption and use in the United Arab Emirates.

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological bulletin*, *103*(3), 411.

Azizi, S. M., Soroush, A., & Khatony, A. (2019). The relationship between social networking addiction and academic performance in Iranian students of medical sciences: a cross-sectional study. *BMC psychology*, *7*, 1-8.

Baabdullah, A. M., Alalwan, A. A., Rana, N. P., Kizgin, H., & Patil, P. (2019). Consumer use of mobile banking (M-Banking) in Saudi Arabia: Towards an integrated model. *International journal of information management*, *44*, 38-52.

Bagozzi, R. P., & Phillips, L. W. (1982). Representing and testing organizational theories: A holistic construal. *Administrative science quarterly*, 459-489.

Baishya, K., & Samalia, H. V. (2020). Extending unified theory of acceptance and use of technology with perceived monetary value for smartphone adoption at the bottom of the pyramid. *International Journal of Information Management*, *51*, 102036.

Bajaj, A., & Nidumolu, S. R. (1998). A feedback model to understand information system usage. *Information & management*, *33*(4), 213-224.

Bandoh, S. O., Akweittey, E., Lotey, E. K., Gordon, J. F., & Appiagyei, E. (2024). Using UTAUT model to assess the factors influencing the use of ICT in Ghanaian pre-tertiary mathematics education. *Journal of Digital Educational Technology*, *4*(1), ep2407. https://doi.org/10.30935/jdet/14297

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review*.

Bandura, A. (1978). The self system in reciprocal determinism. *American psychologist*, *33*(4), 344.

Bandura, A. (1982). Self-efficacy mechanism in human agency. *American psychologist*, *37*(2), 122.

Bandura, A. (1986). Fearful expectations and avoidant actions as coeffects of perceived self-inefficacy.

Bandura, A. (1986). The explanatory and predictive scope of self-efficacy theory. *Journal of social and clinical psychology*, *4*(3), 359-373.

Bandura, A. (1989). Human agency in social cognitive theory. *American psychologist*, *44*(9), 1175.

Bandura, A. (1986). Social foundations of thought and action. *Englewood Cliffs, NJ*, *1986*(23-28), 2.

Bandura, A. (1977). Social learning theory. *Englewood Cliffs*.

Bandura, A. (1997). Self-efficacy: The exercise of control. W. H. Freeman.

Baptista, G., & Oliveira, T. (2015). Understanding mobile banking: The unified theory of acceptance and use of technology combined with cultural moderators. *Computers in human behavior*, *50*, 418-430.

Barron, A. E., Kemker, K., Harmes, C., & Kalaydjian, K. (2003). Large-scale research study on technology in K–12 schools: Technology integration as it relates to the National Technology Standards. *Journal of Research on Technology in Education*, *35*(4), 489-507.

Barton, R. F. (1955). The mythology of the Ifugaos.

Baruch, Y., & Holtom, B. C. (2008). Survey response rate levels and trends in organizational research. *Human relations*, *61*(8), 1139-1160.

Baskara, F. R. (2023). Integrating ChatGPT into EFL writing instruction: Benefits and challenges. *International Journal of Education and Learning*, *5*(1), 44–55. https://doi.org/10.31763/ijele.v5i1.858

Bayaga, A., & Du Plessis, A. (2024). Ramifications of the Unified Theory of Acceptance and Use of Technology (UTAUT) among developing countries' higher education staffs. *Education and Information Technologies*, *29*(8), 9689–9714. https://doi.org/10.1007/s10639-023-12194-6

Bayag, A., & Madimabe, M. (2024). Unified theory of acceptance and use of technology (UTAUT) model as means to maximise teacher collaboration in the indigenisation of mathematics pedagogy. *South African Journal of Higher Education*, *38*(3), 46-63.

Becker, J. M., Rai, A., & Rigdon, E. (2013). Predictive validity and formative measurement in structural equation modeling: Embracing practical relevance.

Ben Williamson (2016) Digital education governance: data visualization, predictive analytics, and 'real-time' policy instruments, *Journal of Education Policy*, 31:2, 123-141, DOI: 10.1080/02680939.2015.1035758

Benbasat, I., Goldstein, D.K., and Mead, M. "The Case Research Strategy in Studies of Information Systems," *MIS Quarterly* (11:3), 1987, pp. 368-386.

Bendig, A. W. (1954). Reliability and the number of rating-scale categories. *Journal of Applied Psychology*, 38(1), 38.

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin*, 107(2), 238.

Bentler, P. M., & Bonett, D. G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. *Psychological Bulletin*, 88(3), 588.

Birkett, N. J. (1986, January). Selecting the number of response categories for a Likert-type scale. In *Proceedings of the American statistical association* (Vol. 1, No. 1, pp. 488-492).

Blais, M. R., Sabourin, S., Boucher, C., & Vallerand, R. J. (1990). Toward a motivational model of couple happiness. *Journal of Personality and Social psychology*, 59, 1021-1031.

Blank, G., & Groselj, D. (2014). Dimensions of Internet use: amount, variety, and types. *Information, Communication & Society*, 17(4), 417-435.

Blank, G., & Groselj, D. (2015). Digital divide Examining internet use through a Weberian lens. *International Journal of Communication*, 9, 21.

Bollen, K. A. (1989). *Structural equations with latent variables* (Vol. 210). John Wiley & Sons.

Bollen, K. A., & Paxton, P. (2000). Subjective measures of liberal democracy. *Comparative political studies*, *33*(1), 58-86.

Borisenkov, V. P. (2015). Education quality and issues of pedagogical staff training. *The Education and Science Journal*, 1(3), 4-28.

Bosse, T., Gerritsen, C., & Klein, M. C. (2010). Predicting the development of juvenile delinquency by simulation. In *Trends in Applied Intelligent Systems: 23rd International Conference on Industrial Engineering and Other Applications of Applied Intelligent Systems, IEA/AIE 2010, Cordoba, Spain, June 1-4, 2010, Proceedings, Part II 23* (pp. 565-574). Springer Berlin Heidelberg.

Botha, D. F., & Fouché, B. (2002). Knowledge management practices in the South African business sector: preliminary findings of a longitudinal study. *South African Journal of Business Management*, 33(2), 13-19.

Brettel, M., Engelen, A., Heinemann, F., & Vadhanasindhu, P. (2008). Antecedents of market orientation: A cross-cultural comparison. *Journal of International Marketing*, 16(2), 84-119.

Brown, B. B., Larson, R. W., & Saraswathi, T. S. (Eds.). (2002). *The world's youth: Adolescence in eight regions of the globe*. Cambridge University Press.

Brown, S. A., & Venkatesh, V. (2005). Model of adoption of technology in households: A baseline model test and extension incorporating household life cycle. *MIS Quarterly*, 399-426.

Browne, M. W., & Cudeck, R. (1992). Alternative ways of assessing model fit. *Sociological Methods & Research*, 21(2), 230-258.

Bell, E., Bryman, A., & Harley, B. (2022). *Business research methods*. Oxford university press.

Buckle, R. A., & Creedy, J. (2019). The evolution of research quality in New Zealand universities as measured by the performance-based research fund process. *New Zealand Economic Papers*, 53(2), 144-165.

Buisseret, T. J., Cameron, H. M., & Georghiou, L. (1995). What difference does it make? Additionality in the public support of R&D in large firms. *International Journal of Technology Management*, 10(4-6), 587-600.

Byrne, B. M. (1994). *Structural equation modeling with EQS and EQS/Windows: Basic concepts, applications, and programming*. sage.

Cacioppo, J. T., Petty, R. E., Feinstein, J. A., & Jarvis, W. B. G. (1996). Dispositional differences in cognitive motivation: The life and times of individuals varying in need for cognition. *Psychological Bulletin*, 119(2), 197.

Camilleri, M. A. (2024). Metaverse applications in education: A systematic review and a cost-benefit analysis. *Interactive Technology and Smart Education*, *21*(2), 245–269. https://doi.org/10.1108/ITSE-01-2023-0017

Cannell, C. F., Miller, P. V., & Oksenberg, L. (1981). Research on interviewing techniques. *Sociological Methodology*, 12, 389-437.

Cevikbas, M., Bulut, N., & Kaiser, G. (2023). Exploring the Benefits and Drawbacks of AR and VR Technologies for Learners of Mathematics: Recent Developments. *Systems*, *11*(5), 244. https://doi.org/10.3390/systems11050244

Chadegani, A. A., Salehi, H., Yunus, M. M., Farhadi, H., Fooladi, M., Farhadi, M., & Ebrahim, N. A. (2013). A comparison between two main academic literature collections: Web of Science and Scopus databases. *arXiv preprint arXiv:1305.0377*.

Chaplin, T. M., Hong, K., Bergquist, K., & Sinha, R. (2008). Gender differences in response to emotional stress: an assessment across subjective, behavioral, and physiological domains and relations to alcohol craving. *Alcoholism: Clinical and Experimental Research*, *32*(7), 1242-1250.

Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: Perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education*, *20*(1), 43. https://doi.org/10.1186/s41239-023-00411-8

Chan, W. K., Huang, L., Gudikote, J. P., Chang, Y. F., Imam, J. S., MacLean, J. A., & Wilkinson, M. F. (2007). An alternative branch of the nonsense-mediated decay pathway. *The EMBO journal*, *26*(7), 1820-1830.

Charness, N., & Boot, W. R. (2009). Aging and information technology use: Potential and barriers. *Current directions in psychological science*, *18*(5), 253-258.

Chatterjee, S., Kar, A. K., & Gupta, M. (2018). Success of IoT in smart cities of India: An empirical analysis. *Government Information Quarterly*, 35(3), 349-361.

Chatterjee, S., Kar, A. K., Dwivedi, Y. K., & Kizgin, H. (2019). Prevention of cybercrimes in smart cities of India: from a citizen's perspective. *Information Technology & People*, 32(5), 1153-1183

Chau, P.Y.K., and Hu, P.J. "Investigating Healthcare Professionals' Decisions to Accept Telemedicine Technology: An Empirical Test of Competing Theories," *Information and Management* (39), 2002, pp. 297-311.

Chea, S., & Luo, M. M. (2019). Pleasantness, activation, and negative affectivity: a test of extended UTAUT Model.

Chen, S., Duckworth, K., & Chaiken, S. (1999). Motivated heuristic and systematic processing. *Psychological inquiry*, *10*(1), 44-49.

Cheng, A., Lang, T. R., Starr, S. R., Pusic, M., & Cook, D. A. (2014). Technology-enhanced simulation and pediatric education: a meta-analysis. *Pediatrics*, *133*(5), e1313-e1323.

Cheong, C., Cheong, F., & Filippou, J. (2013). Quick quiz: A gamified approach for enhancing learning.

Childers, T. L., Carr, C. L., Peck, J., & Carson, S. (2001). Hedonic and utilitarian motivations for online retail shopping behavior. *Journal of retailing*, *77*(4), 511-535.

Chin, W. W., & Dibbern, J. (2009). An introduction to a permutation based procedure for multi-group PLS analysis: Results of tests of differences on simulated data and a cross cultural analysis of the sourcing of information system services between Germany and the USA. In *Handbook of partial least squares: Concepts, methods and applications* (pp. 171-193). Berlin, Heidelberg: Springer Berlin Heidelberg.

Chon, K. S. (1989). Understanding recreational traveler's motivation, attitude and satisfaction. *The Tourist Review*, 44(1), 3-7.

Chon, K. S., Evans, M. R., & Sutherlin, D. (1989). Trends in hospitality management literature: A content analysis. *Hospitality Education and Research Journal*, 13(3), 483-491.

Chong, A. Y. L. (2013). Predicting m-commerce adoption determinants: A neural network approach. *Expert Systems with Applications*, 40(2), 523-530.

Chopdar, P. K., & Sivakumar, V. J. (2019). Understanding continuance usage of mobile shopping applications in India: the role of espoused cultural values and perceived risk. *Behaviour & Information Technology*, 38(1), 42-64.

Chopdar, P. K., Korfiatis, N., Sivakumar, V. J., & Lytras, M. D. (2018). Mobile shopping apps adoption and perceived risks: A cross-country perspective utilizing the Unified Theory of Acceptance and Use of Technology. *Computers in Human Behavior*, 86, 109-128.

Chugh, R., Turnbull, D., Cowling, M. A., Vanderburg, R., & Vanderburg, M. A. (2023). Implementing educational technology in Higher Education Institutions: A review of technologies, stakeholder perceptions, frameworks and metrics. *Education and Information Technologies*, *28*(12), 16403–16429. https://doi.org/10.1007/s10639-023-11846-x

Clarke, S. G., & Haworth, J. T. (1994). ‘Flow’experience in the daily lives of sixth-form college students. *British Journal of Psychology*, 85(4), 511-523.

Cohen, J. (1992). Statistical power analysis. *Current Directions in Psychological Science*, 1(3), 98-101.

Compeau, D. R., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS Quarterly*, 189-211.

Compeau, D. R., and Higgins, C. A. “Application of Social Cognitive Theory to Training for Computer Skills,” *Information Systems Research* (6:2), 1995a, pp. 118-143.

Compeau, D. R., Higgins, C. A., and Huff, S. “Social Cognitive Theory and Individual Reactions to Computing Technology: A Longitudinal Study,” *MIS Quarterly* (23:2), 1999, pp. 145-158.

Conner, M., & Sparks, P. (2005). Theory of planned behaviour and health behaviour. *Predicting Health Behaviour*, 2(1), 121-162.

Coombs, R., Knights, D., and Willmott, H.C. “Culture, Control and Completion: Towards a Conceptual Framework for the Study of Information Technology in Organizations,” *Organization Studies* (13:1), 1992, pp. 51-72.

Craighead, C. W., Ketchen, D. J., Dunn, K. S., & Hult, G. T. M. (2011). Addressing common method variance: guidelines for survey research on information technology, operations, and supply chain management. IEEE *Transactions on Engineering Management*, 58(3), 578-588.

Creswell, J. W., & Creswell, J. D. (2017). *Research design: Qualitative, quantitative, and mixed methods approaches*. Sage Publications.

Crompton, J. L. (1979). Motivations for pleasure vacation. *Annals of Tourism Research*, 6(4), 408-424.

Cronbach, L. J. (1955). Processes affecting scores on" understanding of others" and" assumed similarity.". *Psychological Bulletin*, 52(3), 177.

Csikszentmihalyi, M. (1990). Literacy and intrinsic motivation. Daedalus, 115-140.

Csikszentmihalyi, M. (1990). The domain of creativity.

Csikszentmihalyi, M. (1997). Flow and the psychology of discovery and invention. HarperPerennial, New York, 39, 1-16.

Czaja, S. J., Charness, N., Fisk, A. D., Hertzog, C., Nair, S. N., Rogers, W. A., & Sharit, J. (2006). Factors predicting the use of technology: Findings from the Center for Research and Education on Aging and Technology Enhancement (CREATE). *Psychology and Aging*, 21(2), 333–352. https://doi.org/10.1037/0882-7974.21.2.333

Dabbagh, N., & Kitsantas, A. (2012). Personal Learning Environments, social media, and self-regulated learning: A natural formula for connecting formal and informal learning. *The Internet and Higher Education*, 15(1), 3-8.

Da Silva Soares, A., Lerigo-Sampson, M., & Barker, J. (2024). Recontextualising the Unified Theory of Acceptance and Use of Technology (UTAUT) Framework to Higher Education Online Marking. *Journal of University Teaching and Learning Practice*. https://doi.org/10.53761/7ft8x880

Davis, F. D. (1985). A technology acceptance model for empirically testing new end-user information systems: Theory and results (Doctoral dissertation, Massachusetts Institute of Technology).

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 319-340.

Davis, F. D. "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology," *MIS Quarterly* (13:3), 1989, pp. 319-339.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, 35(8), 982-1003.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace 1. *Journal of Applied Social Psychology*, 22(14), 1111-1132.

Dawson, J. F. (2014). Moderation in management research: What, why, when, and how. *Journal of Business and Psychology*, 29(1), 1-19.

De Manzano, Ö., Theorell, T., Harmat, L., & Ullén, F. (2010). The psychophysiology of flow during piano playing. *Emotion*, 10(3), 301.

Deci, E. L. (1971). Effects of externally mediated rewards on intrinsic motivation. *Journal of personality and Social Psychology*, 18(1), 105.

Deci, E. L., & Ryan, R. M. (1985). The general causality orientations scale: Self-determination in personality. *Journal of Research in Personality*, 19(2), 109-134.

DeLone, W. H., and McLean, E.R. “Information Systems Success: the Quest for the Dependent Variable,” *Information Systems Research* (3:1), 1992, pp. 60-95.

Diamantopoulos, A., Sarstedt, M., Fuchs, C., Wilczynski, P., & Kaiser, S. (2012). Guidelines for choosing between multi-item and single-item scales for construct measurement: a predictive validity perspective. *Journal of the Academy of Marketing Science*, 40(3), 434-449.

Diaz, M. C., & Loraas, T. (2010). Learning new uses of technology while on an audit engagement: Contextualizing general models to advance pragmatic understanding. *International Journal of Accounting Information Systems*, 11(1), 61-77.

Dishaw, M.T., and Strong, D.M. “Extending the Technology Acceptance Model with TaskTechnology Fit Constructs,” *Information and Management* (36:1), 1999, pp. 9–21.

Doll, W.J., and Torkzadeh, G. “Developing a Multidimensional Measure of System-Use in an Organizational Context,” *Information and Management* (33: 4), 1998, pp. 171-185.

Duan, C. (2024). Advancing open education through open-source software: Examining UTAUT 2 factors in adoption and implementation. *Asian Association of Open Universities Journal*, *19*(3), 313–326. https://doi.org/10.1108/AAOUJ-09-2024-0119

Duha Khalid Abdul-Rahman Al-Malah, Ban Hassan Majeed, & ALRikabi, H. TH. S. (2023). Enhancement the Educational Technology by Using 5G Networks. *International Journal of Emerging Technologies in Learning (iJET)*, *18*(01), 137–151. https://doi.org/10.3991/ijet.v18i01.36001

Duman, B., & Oğuz, T. (n.d.). *Academicans' Perceptions Towards Online Teaching Tools Within the Context of the Unified Theory of Acceptance and Use of Technology-2 (UTAUT-2)*.

Dwivedi, Y. K., Rana, N. P., Janssen, M., Lal, B., Williams, M. D., & Clement, M. (2017). An empirical validation of a unified model of electronic government adoption (UMEGA). *Government Information Quarterly*, 34(2), 211-230.

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the unified theory of acceptance and use of technology (UTAUT): Towards a revised theoretical model. *Information Systems Frontiers*, 21(3), 719-734.

Dwivedi, Y. K., Shareef, M. A., Simintiras, A. C., Lal, B., & Weerakkody, V. (2016). A generalised adoption model for services: A cross-country comparison of mobile health (m-health). *Government Information Quarterly*, 33(1), 174-187.

Dwivedi, Y. K., Khan, N., & Papazafeiropoulou, A. (2007). Consumer adoption and usage of broadband in Bangladesh. *Electronic Government, an International Journal*, *4*(3), 299-313.

Eagly, A. H. (1993). The psychology of attitudes. *Thomson Wadsworth*.

Eagly, A. H., & Wood, W. (2012). Social role theory. *Handbook of theories of social psychology*, *2*, 458-476.

Eaves, L. J., Last, K. A., Young, P. A., & Martin, N. G. (1978). Model-fitting approaches to the analysis of human behaviour. *Heredity*, 41(3), 249-320.

Edwards, C., Smith, M. G., & Peterson, R. N. (1985). The changing distribution of farms by size: A Markov analysis. *Agricultural Economics Research*, 37(1489-2016-125930), 1-16.

Edwards, J. R. (2001). Multidimensional constructs in organizational behavior research: An integrative analytical framework. *Organizational Research Methods*, 4(2), 144-192.

Edwards, J. R., & Bagozzi, R. P. (2000). On the nature and direction of relationships between constructs and measures. *Psychological Methods*, 5(2), 155.

Elfeky, A. I. M., & Elbyaly, M. Y. H. (2024). The impact of project-based learning on the development of cognitive achievement in the course of applications in educational technology among students of the college of education at najran university. *European Chemical Bulletin*.

El-Gayar, O. F., & Moran, M. (2007). Examining students' acceptance of tablet PC using TAM.

Etikan, I., & Bala, K. (2017). Sampling methods and sample size calculation for logistic regression in medical research. *Biometrics & Biostatistics International Journal*, 5(6), 215–217. https://doi.org/10.15406/bbij.2017.05.00149

Evans, J. R., & Mathur, A. (2018). The value of online surveys: A look back and a look ahead. *Internet research*, *28*(4), 854-887.

Fang, X. (2015, August). Research of the MOOC study behavior influencing factors. In *2015 3d International Conference on Advanced Information and Communication Technology for Education (ICAICTE-2015)* (pp. 18-22). Atlantis Press.

Fathema, N., Shannon, D., & Ross, M. (2015). Expanding the Technology Acceptance Model (TAM) to examine faculty use of Learning Management Systems (LMSs) in higher education institutions. *Journal of Online Learning & Teaching*, 11(2).

Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: a perceived risk facets perspective. *International Journal of Human-Computer Studies*, 59(4), 451-474.

Fishbein, M., & Ajzen, I. (1977). Belief, attitude, intention, and behavior: An introduction to theory and research.

Fornell, C., & Larcker, D. F. (1981). Structural equation models with unobservable variables and measurement error: *Algebra and Statistics*.

Frazier, P. A., Tix, A. P., & Barron, K. E. (2004). " Testing moderator and mediator effects in counseling psychology research": Correction to Frazier et al.(2004).

Gallagher, S. (2008). Inference or interaction: Social cognition without precursors. *Philosophical Explorations*, *11*(3), 163-174.

Gallivan, M.J., Spitler, V.K., and Koufaris, M. "Does Information Technology Training Really Matter? A Social Information Processing Analysis of Coworkers' Influence on IT Usage in the Workplace," *Journal of Management Information Systems* (22:1), 2005, pp. 153-192.

Gao, S., & Yang, Y. (2015). Exploring users' adoption of MOOCs from the perspective of the institutional theory.

García-Mendoza, M. D. C., Parra, A., Sánchez-Queija, I., Oliveira, J. E., & Coimbra, S. (2022). Gender differences in perceived family involvement and perceived family control during emerging adulthood: A cross-country comparison in Southern Europe. *Journal of Child and Family Studies*, 31(4), 1007-1018.

Garfield, E. (1955). Citation indexes for science: A new dimension in documentation through association of ideas. *Science*, 122(3159), 108-111.

Gaspar, H., Morgado, L., Mamede, H., Oliveira, T., Manjón, B., & Gütl, C. (2019). Research priorities in immersive learning technology: the perspectives of the iLRN community. *Virtual Reality*, 1-23.

Gefen, D., & Straub, D. W. (2000). The relative importance of perceived ease of use in IS adoption: A study of e-commerce adoption. *Journal of the association for Information Systems*, 1(1), 8.

Gefen, D., & Straub, D. W. (2004). Consumer trust in B2C e-Commerce and the importance of social presence: experiments in e-Products and e-Services. *Omega*, 32(6), 407-424.

Gefen, D., and Straub, D.W. "Gender differences in the perception and use of e-mail: An Extension to the Technology Acceptance Model," *MIS Quarterly* (21:4), 1997, pp. 389-400.

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS quarterly*, 51-90.

George, D. (2011). *SPSS for windows step by step: A simple study guide and reference, 17.0 update, 10/e*. Pearson Education India.

Georghiou, L. (1998). Global cooperation in research. *Research Policy*, 27(6), 611-626.

Ghani, J. A., & Deshpande, S. P. (1994). Task characteristics and the experience of optimal flow in human—computer interaction. *The Journal of Psychology*, 128(4), 381-391.

Gibbons, M., & Georghiou, L. (1987). *Evaluation of Research. A Selection of Current Practices*. OECD Publications Service, Sales and Distribution Division, 2, rue Andre-Pascal, 75775 Paris, France..

Givon, M. M., & Shapira, Z. (1984). Response to rating scales: A theoretical model and its application to the number of categories problem. *Journal of Marketing Research*, 21(4), 410-419.

Godin, G., & Kok, G. (1996). The theory of planned behavior: a review of its applications to health-related behaviors. *American Journal of Health Promotion*, 11(2), 87-98.

Goffin, K., & Mitchell, R. (2010). Innovation management. NY: Palgrave Macmillan, 416.

Gong, X., Lee, M. K., Liu, Z., & Zheng, X. (2020). Examining the role of tie strength in users' continuance intention of second-generation mobile instant messaging services. *Information Systems Frontiers*, *22*, 149-170.

Gopalakrishna-Remani, V., Jones, R. P., & Camp, K. M. (2019). Levels of EMR adoption in US hospitals: An empirical examination of absorptive capacity, institutional pressures, top management beliefs, and participation. *Information Systems Frontiers*, 21(6), 1325-1344.

Grandon, E.E., and Pearson, J. M. "Electronic commerce adoption: an empirical study of small and medium US business," *Information and Management* (42) 2004, pp. 197-216.

Green, K. C., & Gilbert, S. W. (1995). Great expectations: Content, communications, productivity, and the role of information technology in higher education. Change: *The Magazine of Higher Learning*, 27(2), 8-18.

Green, P. E., & Rao, V. R. (1970). Rating scales and information recovery—How many scales and response categories to use?. *Journal of Marketing*, 34(3), 33-39.

Gruzd, A., Staves, K., & Wilk, A. (2012). Connected scholars: Examining the role of social media in research practices of faculty using the UTAUT model. *Computers in Human Behavior*, 28(6), 2340-2350.

Guo, Y. M., & Ro, Y. K. (2008). Capturing flow in the business classroom. *Decision Sciences Journal of Innovative Education*, 6(2), 437-462.

Guo, Y., & Barnes, S. (2011). Purchase behavior in virtual worlds: An empirical investigation in Second Life. *Information & Management*, 48(7), 303-312.

Gupta, A. (2008). Constructivism and peer collaboration in elementary mathematics education: The connection to epistemology. *Eurasia Journal of Mathematics, Science and Technology Education*, 4(4), 381-386.

Gupta, A., Yousaf, A., & Mishra, A. (2020). How pre-adoption expectancies shape post-adoption continuance intentions: An extended expectation-confirmation model. *International Journal of Information Management*, 102094.

Gursoy, D., Chi, O. H., Lu, L., & Nunkoo, R. (2019). Consumers acceptance of artificially intelligent (AI) device use in service delivery. *International Journal of Information Management*, 49, 157-169.

Hagenson, L. (2001). The integration of technology into teaching by university college of education faculty (Master thesis, Oklahoma State University, 2001).

Hair Jr, J. F., Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. *European Business Review*.

Hair Jr, J. F., Sarstedt, M., Matthews, L. M., & Ringle, C. M. (2016). Identifying and treating unobserved heterogeneity with FIMIX-PLS: part I–method. *European Business Review*.

Hair, E., Halle, T., Terry-Humen, E., Lavelle, B., & Calkins, J. (2006). Children's school readiness in the ECLS-K: Predictions to academic, health, and social outcomes in first grade. *Early Childhood Research Quarterly*, 21(4), 431-454.

Hair, J. F. (2011). Multivariate data analysis: An overview. *International Encyclopedia of Statistical Science*, 904-907.

Hair, J. F., Ortinau, D. J., & Harrison, D. E. (2010). *Essentials of marketing research* (Vol. 2). New York, NY: McGraw-Hill/Irwin.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2013). Partial least squares structural equation modeling: Rigorous applications, better results and higher acceptance. Long range planning, 46(1-2), 1-12.

Hamari, J., Shernoff, D. J., Rowe, E., Coller, B., Asbell-Clarke, J., & Edwards, T. (2016). Challenging games help students learn: An empirical study on engagement, flow and immersion in game-based learning. *Computers in Human Behavior*, 54, 170-179.

Hartwick, J., and Barki, H. "Explaining the Role of User Participation in Information System Use," Management Science (40:4), 1994, pp. 440-465.

Hayduk, L., Cummings, G., Boadu, K., Pazderka-Robinson, H., & Boulianne, S. (2007). Testing! testing! one, two, three–Testing the theory in structural equation models!. *Personality and Individual Differences*, 42(5), 841-850.

Heidt, M., Gerlach, J. P., & Buxmann, P. (2019). Investigating the security divide between SME and large companies: How SME characteristics influence organizational IT security investments. *Information Systems Frontiers*, 21(6), 1285-1305.

Helgeson, V. S. (1994). Relation of agency and communion to well-being: Evidence and potential explanations. *Psychological Bulletin*, 116(3), 412–428. https://doi.org/10.1037/0033-2909.116.3.412

Hendrickson, A. R., Massey, P. D., & Cronan, T. P. (1993). On the test-retest reliability of perceived usefulness and perceived ease of use scales. *MIS Quarterly*, 227-230.

Henseler, J., & Chin, W. W. (2010). A comparison of approaches for the analysis of interaction effects between latent variables using partial least squares path modeling. *Structural Equation Modeling*, 17(1), 82-109.

Herrington, J., & Oliver, R. (2000). An instructional design framework for authentic learning environments. *Educational Technology Research and Development*, 48(3), 23-48.

Hicks, D., Wouters, P., Waltman, L., De Rijcke, S., & Rafols, I. (2015). Bibliometrics: the Leiden Manifesto for research metrics. *Nature*, 520(7548), 429-431.

Hinkin, T. R. (1998). A brief tutorial on the development of measures for use in survey questionnaires. *Organizational Research Methods*, 1(1), 104-121.

Hirschheim R., and Klein H. K. "Four Paradigms of Information Systems Development," Communications of the ACM (32:10), 1989, pp. 1199-1216.

Hoffman, D. L., & Novak, T. (2016). How to market the smart home: focus on emergent experience, not use cases. Not Use Cases (January 15, 2016).

Hoffman, D. L., & Novak, T. P. (1996). Marketing in hypermedia computer-mediated environments: Conceptual foundations. *Journal of Marketing*, 60(3), 50-68.

Hoi, V. N. (2020). Understanding higher education learners' acceptance and use of mobile devices for language learning: A Rasch-based path modeling approach. *Computers & Education*, 146, 1-15.

Hossain, A., Quaresma, R., & Rahman, H. (2019). Investigating factors influencing the physicians' adoption of electronic health record (EHR) in healthcare system of Bangladesh: An empirical study. *International Journal of Information Management*, 44, 76-87.

Hooper, D., Coughlan, J., & Mullen, M. (2008, September). Evaluating model fit: a synthesis of the structural equation modelling literature. In 7th European Conference on research methodology for business and management studies (pp. 195-200).

Hooper, D., Coughlan, J., & Mullen, M. R. (2008). Structural equation modelling: Guidelines for determining model fit. *Electronic Journal of Business Research Methods*, 6(1), pp53-60.

Horn, J. L., & McArdle, J. J. (1992). A practical and theoretical guide to measurement invariance in aging research. *Experimental Aging Research*, 18(3), 117-144.

Hossain, M. A., Dwivedi, Y. K., Chan, C., Standing, C., & Olanrewaju, A. S. (2018). Sharing political content in online social media: A planned and unplanned behaviour approach. *Information Systems Frontiers*, 20(3), 485-501.

Hrastinski, S., & Keller, C. (2007). Computer-mediated communication in education: A review of recent research. *Educational Media International*, 44(1), 61-77.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, 6(1), 1-55.

Hu, P. J., Chau, P. Y. K., Sheng, O. R. L., and Tam, K. Y. "Examining the Technology Acceptance Model Using Physician Acceptance of Telemedicine Technology," *Journal of Management Information Systems* (16:2), 1999, pp. 91-112.

Huang, J. H., Lin, Y. R., & Chuang, S. T. (2007). Elucidating user behavior of mobile learning: A perspective of the extended technology acceptance model. *The Electronic Library*.

Huseynov, F., & Özkan Yıldırım, S. (2019). Online consumer typologies and their shopping behaviors in B2C e-commerce platforms. *SAGE Open*, 9(2), 9.

Hyde, J. S. (2014). Gender similarities and differences. *Annual Review of Psychology*, 65(1), 373–398. https://doi.org/10.1146/annurev-psych-010213-115057

Hylén, J. (2006). Open Educational Resources: Opportunities and Challenges. Paris: OECD's Center for Educational Research and Innovation. (Polit & Beck, 2006).

Igbaria, M., Zinatelll, N., Cragg, P., and Cavaye, A. “Personal Computing Acceptance Factors in Small Firms: a Structural Equation Model,” *MIS Quarterly* (21: 3), 1997, pp. 279-302.

Imtiaz, M. A., & Maarop, N. (2014). A review of technology acceptance studies in the field of education. *Jurnal Teknologi*, 69(2).

Ing, P., & Shien, G. Y. (2019). Offline brand outcomes of Instagram: Do cognitive network and self-congruity matter?. *Asian Journal of Business and Accounting*, 12(2), 287-314.

Jackson, C.M., Chow, S., and Leitch, R.A. “Toward an Understanding of the Behavioral Intention to Use an Information System,” *Decision Sciences* (28:2), 1997, pp. 357-389.

Jacoby, J., & Matell, M. S. (1971). Three-point Likert scales are good enough.

Jairak, R., Praneetpolgrang, P., & Mekhabunchakij, K. (2009, December). An investigation of trust in e-learning for instructors and students in private and public universities. In Proc. 6th elearning for knowledge-based society conf., Thailand (pp. 17-18).

Jappe, A. (2020). Professional standards in bibliometric research evaluation? A meta-evaluation of European assessment practice 2005–2019. PloS one, 15(4), e0231735.

Jappe, A., Pithan, D., & Heinze, T. (2018). Does bibliometric research confer legitimacy to research assessment practice? A sociological study of reputational control, 1972-2016. *PloS One*, 13(6), e0199031.

Jasperson, J., Carter, P. E., & Zmud, R. W. (2005). A comprehensive conceptualization of post-adoptive behaviors associated with information technology enabled work systems. *MIS Quarterly*, 525-557.

Jenkins, G. D., & Taber, T. D. (1977). A Monte Carlo study of factors affecting three indices of composite scale reliability. *Journal of Applied Psychology*, 62(4), 392.

Jhurree, V. (2005). Technology integration in education in developing countries: Guidelines to policy makers. *International Education Journal*, 6(4), 467–483.

Joo, Y. J., Lim, K. Y., & Kim, J. (2013). Locus of control, self-efficacy, and task value as predictors of learning outcome in an online university context. *Computers & Education*, 62, 149-158.

Jöreskog, K. G., & Yang, F. (2013). Nonlinear structural equation models: The Kenny–Judd model with interaction effects. In *Advanced structural equation modeling* (pp. 57-88). Psychology Press.

Jurowski, C., Uysal, M., & Noe, F. P. (1993). US Virgin Islands National Park: A factor-cluster segmentation study. *Journal of Travel & Tourism Marketing*, 1(4), 3-31.

Kaffashi, S., & Shamsudin, M. N. (2019). Transforming to a low carbon society; an extended theory of planned behaviour of Malaysian citizens. *Journal of Cleaner Production*, 235, 1255-1264.

Kapoor, K. K., & Dwivedi, Y. K. (2020). Sustainable consumption from the consumer's perspective: Antecedents of solar innovation adoption. *Resources, Conservation and Recycling*, 152, 104501.

Karahanna, E., and Straub, D. W. "The Psychological Origins of Perceived Usefulness and Ease of Use," *Information and Management* (35:4), 1999, pp. 237-250. 17

Karahanna, E., Straub, D. W., & Chervany, N. L. (1999). Information technology adoption across time: A cross-sectional comparison of pre-adoption and post-adoption beliefs. *MIS Quarterly*, 183-213.

Karakoyun, F., & Başaran, B. (2024). Profiling University Students' Technology Acceptance Through UTAUT. *Malaysian Online Journal of Educational Technology*, *12*(2), 78–92. https://doi.org/10.52380/mojet.2024.12.2.550

Karmiloff-Smith, B. A. (1994). Beyond modularity: A developmental perspective on cognitive science. *European Journal of Disorders of Communication*, 29(1), 95-105.

Kaushik, K., Mishra, R., Rana, N. P., & Dwivedi, Y. K. (2018). Exploring reviews and review sequences on e-commerce platform: A study of helpful reviews on Amazon.in. *Journal of Retailing and Consumer Services*, 45, 21-32.

Kaveri, A., Gunasekar, S., Gupta, D., & Pratap, M. (2016, December). Decoding engagement in MOOCs: an indian learner perspective. In 2016 IEEE Eighth International Conference on Technology for Education (T4E) (pp. 100-105). IEEE.

Keil, M., Beranek, P.M., and Konsynski, B.R. "Usefulness and Ease of Use – Field Study Evidence Regarding Task Considerations," Decision Support Systems (13:1), 1995a, pp. 75-91.

Keil, M., Tan, B. C., Wei, K. K., Saarinen, T., Tuunainen, V., & Wassenaar, A. (2000). A cross-cultural study on escalation of commitment behavior in software projects. *MIS Quarterly*, 299-325.

Kelman, H. C. "Compliance, Identification, and Internalization: Three processes of Attitude Change," *Journal of Conflict Resolution* (2), 1958, pp. 51-60.

Keong, M. L., Ramayah, T., Kurnia, S., & Chiun, L. M. (2012). Explaining intention to use an enterprise resource planning (ERP) system: an extension of the UTAUT model. *Business Strategy Series*.

Ketcham, C. M., & Crawford, J. M. (2007). The impact of review articles. *Laboratory Investigation*, 87(12), 1174-1185.

Khalifa, M., & Shen, K. N. (2008). Explaining the adoption of transactional B2C mobile commerce. *Journal of Enterprise Information Management*.

Khan, S. H., Hayat, M., Bennamoun, M., Sohel, F. A., & Togneri, R. (2017). Cost-sensitive learning of deep feature representations from imbalanced data. *IEEE Transactions on Neural Networks and Learning Systems*, 29(8), 3573-3587.

Khechine, H., Raymond, B., & Augier, M. (2020). The adoption of a social learning system: Intrinsic value in the UTAUT model. *British Journal of Educational Technology*, 51(6), 2306-2325.

Khine, M. S. (2013). Structural equation modeling approaches in educational research and practice. In Application of structural equation modeling in educational research and practice (pp. 277-283). Brill.

Kline, R. B. (1998). Structural equation modeling. New York: Guilford.

Kline, R. B. (2015). The mediation myth. Basic and Applied Social Psychology, 37(4), 202-213.

Kock, N., & Hadaya, P. (2018). Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. *Information Systems Journal*, 28(1), 227-261.

Komorita, S. S. (1963). Attitude content, intensity, and the neutral point on a Likert scale. *The Journal of Social Psychology*, 61(2), 327-334.

Komorita, S. S., & Graham, W. K. (1965). Number of scale points and the reliability of scales. *Educational and Psychological Measurement*, 25(4), 987-995.

Konanchuk, D. S. (2013). EdTech: new technological platform in education. *University Management: Practice and Analysis*.

Koufaris, M. (2002). Applying the technology acceptance model and flow theory to online consumer behavior. *Information Systems Research*, 13(2), 205-223.

Krosnick, J. A. (1991). Response strategies for coping with the cognitive demands of attitude measures in surveys. *Applied Cognitive Psychology*, 5(3), 213-236.

Kuncel, R. B. (1973). Response processes and relative location of subject and item. *Educational and Psychological Measurement*, 33(3), 545-563.

Langfeldt, L., Nedeva, M., Sörlin, S., & Thomas, D. A. (2020). Co-existing notions of research quality: A framework to study context-specific understandings of good research. *Minerva*, 58(1), 115-137.

Lapointe, L., and Rivard, S. "A Multilevel Model of Resistance to Information Technology Implementation," *MIS Quarterly* (29:3), 2005, pp. 461-491.

Latham, G. P., & Saari, L. M. (1979). Application of social-learning theory to training supervisors through behavioral modeling. *Journal of Applied Psychology*, 64(3), 239.

Lee, Y., Kozar, K. A., & Larsen, K. R. (2003). The technology acceptance model: Past, present, and future. *Communications of the Association for Information Systems*, 12(1), 50.

Leedy, P. D., & Ormrod, J. E. (2001). Practical research: Planning and research. *Upper Saddle*.

Legris, P., Ingham, J., and Collerette, P. "Why Do People Use Information Technology? A Critical Review of the Technology Acceptance Model," *Information & Management* (40:3), 2003, pp. 191-204.

Lehmann, D. R., & Hulbert, J. (1972). Are three-point scales always good enough?. *Journal of Marketing Research*, 9(4), 444-446.

Leong, L.-Y., Hew, T.-S., Ooi, K.-B., Lee, V.-H., & Hew, J.-J. (2019). A hybrid SEM-neural network analysis of social media addiction. *Expert Systems with Applications*, 133, 296-316.

Leydesdorff, L., & Wagner, C. S. (2008). International collaboration in science and the formation of a core group. *Journal of Informetrics*, 2(4), 317-325.

Liao, H., & Chuang, A. (2004). A multilevel investigation of factors influencing employee service performance and customer outcomes. *Academy of Management Journal*, 47(1), 41-58.

Likert, R. (1932). A technique for the measurement of attitudes. *Archives of Psychology*.

Lin, K. Y., Yu, K. C., Hsiao, H. S., Chu, Y. H., Chang, Y. S., & Chien, Y. H. (2015). Design of an assessment system for collaborative problem solving in STEM education. *Journal of Computers in Education*, 2, 301-322.

Lin, Y., & Yu, Z. (2023). Extending Technology Acceptance Model to higher-education students' use of digital academic reading tools on computers. *International Journal of Educational Technology in Higher Education*, *20*(1), 34. https://doi.org/10.1186/s41239-023-00403-8

Lissitz, R. W., & Green, S. B. (1975). Effect of the number of scale points on reliability: A Monte Carlo approach. *Journal of Applied Psychology*, 60(1), 10.

Lithoxoidou, E., Doumpoulakis, S., Tsakiris, A., Ziogou, C., Krinidis, S., Paliokas, I., ... & Tzovaras, D. (2020). A novel social gamified collaboration platform enriched with shop-floor data and feedback for the improvement of the productivity, safety and engagement in factories. *Computers & Industrial Engineering*, 139, 105691.

Liu, C., Forsythe, S., & Black, W. C. (2011). Beyond adoption: sustaining online shopping. *The International Review of Retail, Distribution and Consumer Research*, 21(1), 71-93.

Liu, E., Yan, C., Mei, X., He, W., Bing, S. H., Ding, L., ... & Fan, T. (2010). Long-term effect of chemical fertilizer, straw, and manure on soil chemical and biological properties in northwest China. *Geoderma*, 158(3-4), 173-180.

Lo, C. K. (2020). Systematic reviews on flipped learning in various education contexts. Systematic reviews in educational research: *Methodology, Perspectives and Application*, 129-143.

Lu, H. P., Hsu, C. L., & Hsu, H. Y. (2005). An empirical study of the effect of perceived risk upon intention to use online applications. *Information Management & Computer Security*.

Lucas, H.C.J. and Spitler, V.K. "Technology Use and Performance: A field Study of Broker Workstations," *Decision Sciences* (30:2), 1999, pp. 291-311.

Lujja, S., Mohammad, M. O., & Hassan, R. (2016). Modelling public behavioral intention to adopt Islamic banking in Uganda: the theory of reasoned action. *International Journal of Islamic and Middle Eastern Finance and Management*.

Luo, N., Zhang, M., & Qi, D. (2017). Effects of different interactions on students' sense of community in e-learning environment. *Computers & Education*, 115, 153-160.

Maldonado, S., & Weber, R. (2009). A wrapper method for feature selection using support vector machines. *Information Sciences*, 179(13), 2208-2217.

Maldonado, S., Weber, R., & Famili, F. (2014). Feature selection for high-dimensional class-imbalanced data sets using support vector machines. *Information Sciences*, 286, 228-246.

Man, I. W. C., & Zainuddin, S. (2024). Examining Accounting Educators' Intentions and Usage of Digital Technology: An Empirical Study Using the UTAUT Model. *Asian Journal of Education and Social Studies*, *50*(9), 1–14. https://doi.org/10.9734/ajess/2024/v50i91565

Mann, R. B., & Decker, P. J. (1984). The effect of key behavior distinctiveness on generalization and recall in behavior modeling training. *Academy of Management Journal*, 27(4), 900-910.

Manz, C. C., & Sims Jr, H. P. (1986). Leading self-managed groups: A conceptual analysis of a paradox. *Economic and Industrial Democracy*, 7(2), 141-165.

Marangunić, N., & Granić, A. (2015). Technology acceptance model: a literature review from 1986 to 2013. *Universal Access in The Information Society*, 14, 81-95.

Martin, B. R., & Irvine, J. (1983). Assessing basic research: some partial indicators of scientific progress in radio astronomy. *Research Policy*, 12(2), 61-90.

MASTERS, E. R. (1974). The relationship between number of response categories and reliability of Likert-type questionnaires 1. *Journal of Educational Measurement*, 11(1), 49-53.

Matell, M. S., & Jacoby, J. (1971). Is there an optimal number of alternatives for Likert scale items? Study I: Reliability and validity. *Educational and Psychological Measurement*, 31(3), 657-674.

Mathieson, K. "Predicting User Intentions: Comparing the Technology Acceptance Model with the Theory of Planned Behavior," *Information Systems Research* (2:3), 1991, pp. 173-191.

McDonald, R. P., & Ho, M. H. R. (2002). Principles and practice in reporting structural equation analyses. *Psychological Methods*, 7(1), 64.

McIntosh, C. N. (2007). Rethinking fit assessment in structural equation modelling: A commentary and elaboration on Barrett (2007). *Personality and Individual Differences*, 42(5), 859-867.

McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). The impact of initial consumer trust on intentions to transact with a web site: a trust building model. *The Journal of Strategic Information Systems*, 11(3-4), 297-323.

McKnight, D. H., Cummings, L. L., & Chervany, N. L. (1998). Initial trust formation in new organizational relationships. *Academy of Management Review*, 23(3), 473-490.

Mehta, A., Morris, N. P., Swinnerton, B., & Homer, M. (2019). The Influence of Values on Elearning Adoption. *Computers & Education*, 141, 103617.

Meyer, H. H., & Raich, M. S. (1983). An objective evaluation of a behavior modeling training program. *Personnel Psychology*, 36(4), 755-761.

Mikalef, P., Ilias, P. O., Giannakos, M., Krogstie, J., & Lekakos, G. (2016). Big data and strategy: a research framework.

Miles, J., & Shevlin, M. (2007). A time and a place for incremental fit indices. *Personality and Individual Differences*, 42(5), 869-874.

Miller, J. (1982). Divided attention: Evidence for coactivation with redundant signals. *Cognitive Psychology*, 14(2), 247-279.

Ministry of Human Resource development-(MHRD) (2020). National Education Policy 2020. Government of India.

Miranda, R., & Garcia-Carpintero, E. (2018). Overcitation and overrepresentation of review papers in the most cited papers. *Journal of Informetrics*, 12(4), 1015-1030.

Mishra, S. (2017). Technology enabled learning: Policy, pedagogy and practice. UNESCO.

Moed, H. F., W. J. M. Burger, J. G. Frankfort & A. F. J. van Raan: The application of bibliometric indicators: Important field- and time-dependent factors to be considered. *Scientometrics* 1985a, 8, 177–203.

Moher, D. (2018). Reporting guidelines: doing better for readers. *BMC Medicine*, 16(1), 1-3.

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. Information systems research, 2(3), 192-222.

Moore, G. C., & Benbasat, I. (1996). Integrating diffusion of innovations and theory of reasoned action models to predict utilization of information technology by end-users. In *Diffusion and Adoption of Information Technology: Proceedings of the first IFIP WG 8.6 working conference on the diffusion and adoption of information technology, Oslo, Norway, October 1995* (pp. 132-146). Springer US.

Morris, M. G., & Venkatesh, V. (2000). Age differences in technology adoption decisions: Implications for a changing work force. *Personnel Psychology*, 53(2), 375-403.

Morris, M. G., Venkatesh, V., & Ackerman, P. L. (2005). Gender and age differences in employee decisions about new technology: An extension to the theory of planned behavior. *IEEE Transactions on Engineering Management*, 52(1), 69–84. https://doi.org/10.1109/TEM.2004.839967

Mulaik, S. A., James, L. R., Van Alstine, J., Bennett, N., Lind, S., & Stilwell, C. D. (1989). Evaluation of goodness-of-fit indices for structural equation models. *Psychological Bulletin*, 105(3), 430.

Mulik, S., Yajnik, N., y Godse, M. (2016). Determinants of Acceptance of Massive Open Online Courses. 2016 *IEEE Eighth International Conference on Technology for Education*. Mumbai, India. (T4E). doi:10.1109/t4e.2016.032

Mumtaz, S. (2000). Factors affecting teachers' use of information and communications technology: A review of the literature. *Journal of Information Technology for Teacher Education*, 9(3), 319–342. https://doi.org/10.1080/14759390000200096

Mykytyn Jr, P. P., & Harrison, D. A. (1993). The application of the theory of reasoned action to senior management and strategic information systems. *Information Resources Management Journal* (IRMJ), 6(2), 15-26.

Narin, F. (1976). Evaluative bibliometrics: The use of publication and citation analysis in the evaluation of scientific activity (pp. 206-219). Cherry Hill, NJ: *Computer Horizons*.

Nesterenko, I. (2023). Major benefits of using smart technologies in education. *Scientific Bulletin of Mukachevo State University Series "Pedagogy and Psychology," 9*(1). https://doi.org/10.52534/msu-pp1.2023.31

Ng, T. W., & Feldman, D. C. (2008). The relationship of age to ten dimensions of job performance. *Journal of Applied Psychology*, 93(2), 392–423. https://doi.org/10.1037/0021-9010.93.2.392

Nghiem, N. A., Chen, S. Y. C., & Wei, T. C. (2020). A Unified Framework for Quantum Supervised Learning. arXiv preprint arXiv:2010.13186.

Nistor, N., Baltes, B., Dascălu, M., Mihăilă, D., Smeaton, G., & Trăuşan-Matu, Ş. (2014). Participation in virtual academic communities of practice under the influence of technology acceptance and community factors. A learning analytics application. *Computers in Human Behavior*, 34, 339-344.

Nor, K. M., & Pearson, J. M. (2008). An exploratory study into the adoption of internet banking in a developing country: *Malaysia. Journal of Internet Commerce*, 7(1), 29-73.

Nov, O., & Ye, C. (2009). Resistance to change and the adoption of digital libraries: An integrative model. *Journal of the American Society for Information Science and Technology*, 60(8), 1702-1708.

Novak, T. P., Hoffman, D. L., & Duhachek, A. (2003). The influence of goal-directed and experiential activities on online flow experiences. *Journal of Consumer Psychology*, 13(1-2), 3-16.

Novak, T. P., Hoffman, D. L., & Yung, Y. F. (2000). Measuring the customer experience in online environments: A structural modeling approach. *Marketing Science*, 19(1), 22-42.

Nunnally, J. C. (1994). The assessment of reliability. *Psychometric Theory*.

Olijnyk, N. V. (2015). A quantitative examination of the intellectual profile and evolution of information security from 1965 to 2015. *Scientometrics*, 105(2), 883-904.

Olson, J. M., & Zanna, M. P. (1993). Attitudes and attitude change. *Annual Review of Psychology*, 44, 117.

Olsson, U. H., Foss, T., Troye, S. V., & Howell, R. D. (2000). The performance of ML, GLS, and WLS estimation in structural equation modeling under conditions of misspecification and nonnormality. *Structural Equation Modeling*, 7(4), 557-595.

Osgood, C. E., Suci, G. J., & Tannenbaum, P. H. (1957). The measurement of meaning (No. 47). *University of Illinois Press*.

Ostrom, T. M., & Gannon, K. M. (1996). Exemplar generation: Assessing how respondents give meaning to rating scales.

Pai, J. C., & Tu, F. M. (2011). The acceptance and use of customer relationship management (CRM) systems: An empirical study of distribution service industry in Taiwan. *Expert Systems with Applications*, 38(1), 579-584.

Pan, Y., & He, W. (2024). Research on the influencing factors of promoting flipped classroom teaching based on the integrated UTAUT model and learning engagement theory. *Scientific Reports*, *14*(1), 15201. https://doi.org/10.1038/s41598-024-66214-7

Papert, S. (1987). Information technology and education: Computer criticism vs. technocentric thinking. *Educational Researcher*, 16(1), 22-30.

Patil, H., & Undale, S. (2023). Willingness of university students to continue using e-Learning platforms after compelled adoption of technology: Test of an extended UTAUT model. *Education and Information Technologies*, *28*(11), 14943–14965. https://doi.org/10.1007/s10639-023-11778-6

Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International Journal of Electronic Commerce*, 7(3), 101-134.

Pendlebury, D. A. (2009). The use and misuse of journal metrics and other citation indicators. *Archivum Immunologiae et Therapiae Experimentalis*, 57(1), 1-11.

Persson, O., Glänzel, W., & Danell, R. (2004). Inflationary bibliometric values: The role of scientific collaboration and the need for relative indicators in evaluative studies. *Scientometrics*, 60(3), 421-432.

Peslak, A., Ceccucci, W., & Sendall, P. (2010). An empirical study of instant messaging (IM) behavior using theory of reasoned action. *Journal of Behavioral and Applied Management*, 11(3), 263-278.

Phillips, W. (2015). This is why we can't have nice things: Mapping the relationship between online trolling and mainstream culture. *MIT Press*.

Phuangthong, D., & Malisawan, S. (2005, August). A study of behavioral intention for 3G mobile Internet technology: Preliminary research on mobile learning. In Proceedings of the Second International Conference on eLearning for Knowledge-Based Society (pp. 4-7).

Picciano, A. G., & Spring, J. (2013). The great American education-industrial complex: Ideology, technology, and profit. *Routledge*.

Plageras, A., Xenakis, A., Kalovrektis, K., & Vavougios, D. (2023). An Application Study of the UTAUT Methodology for the Flipped Classroom Model Adoption by Applied Sciences and Technology Teachers. *International Journal of Emerging Technologies in Learning (iJET)*, *18*(02), 190–202. https://doi.org/10.3991/ijet.v18i02.35585

Plouffe, C. R., Hulland, J. S., & Vandenbosch, M. (2001). Richness versus parsimony in modeling technology adoption decisions—understanding merchant adoption of a smart card-based payment system. *Information Systems Research*, 12(2), 208-222.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879.

Polit, D. F., & Beck, C. T. (2006). The content validity index: Are you sure you know what's being reported? critique and recommendations. *Research in Nursing & Health*, *29*(5), 489–497. https://doi.org/10.1002/nur.20147

Polites, G. L., Roberts, N., & Thatcher, J. (2012). Conceptualizing models using multidimensional constructs: a review and guidelines for their use. *European Journal of Information Systems*, 21(1), 22-48.

Porter, L. W., & Lawler, E. E. (1968). What job attitudes tell about motivation (pp. 118-126). Boston, MA, USA: *Harvard Business Review Reprint Service*.

Prasad, D., & Mishra, A. (2018). Digital divide in higher education: A study on infrastructural disparity in Indian universities. *Journal of Educational Technology*, 14(2), 45–56.

Püschel, J., Mazzon, J. A., & Hernandez, J. M. C. (2010). Mobile banking: proposition of an integrated adoption intention framework. *International Journal of Bank Marketing*.

Pynoo, B., Devolder, P., Tondeur, J., Van Braak, J., Duyck, W., & Duyck, P. (2011). Predicting secondary school teachers' acceptance and use of a digital learning environment: A cross-sectional study. *Computers in Human behavior*, 27(1), 568-575.

Queiroz, M. M., & Wamba, S. F. (2019). Blockchain adoption challenges in supply chain: An empirical investigation of the main drivers in India and the USA. *International Journal of Information Management*, 46, 70-82.

Ramsay, J. O. (1973). The effect of number of categories in rating scales on precision of estimation of scale values. *Psychometrika*, 38(4), 513-532.

Rana, N. P., Dwivedi, Y. K., & Williams, M. D. (2013). Evaluating alternative theoretical models for examining citizen centric adoption of e-government. *Transforming Government: People, Process and Policy*, 7(1), 27-49.

Rana, N. P., Dwivedi, Y. K., Lal, B., Williams, M. D., & Clement, M. (2017). Citizens' adoption of an electronic government system: towards a unified view. *Information Systems Frontiers*, 19(3), 549-568.

Rana, N. P., Slade, E., Kitching, S., & Dwivedi, Y. K. (2019). The IT way of loafing in class: Extending the theory of planned behavior (TPB) to understand students' cyberslacking intentions. *Computers in Human Behavior*, 101, 114-123.

Rasoolimanesh, S. M., Jaafar, M., Marzuki, A., & Mohamad, D. (2016). How visitor and environmental characteristics influence perceived crowding. *Asia Pacific Journal of Tourism Research*, 21(9), 952-967.

Rathunde, K., & Csikszentmihalyi, M. (2005). Middle school students' motivation and quality of experience: A comparison of Montessori and traditional school environments. *American Journal of Education*, 111(3), 341-371.

Ravichandran, B., & Shanmugam, K. (2024). Adoption of EdTech products among college students: A conceptual study. *Management Matters*, *21*(1), 1–19. https://doi.org/10.1108/MANM-07-2023-0026

Raykov, T. (1997). Scale reliability, Cronbach's coefficient alpha, and violations of essential tau-equivalence with fixed congeneric components. *Multivariate Behavioral Research*, 32(4), 329-353.

Raza, M. A., Siddiquei, A. N., Awan, H. M., & Bukhari, K. (2012). Relationship between service quality, perceived value, satisfaction and revisit intention in hotel industry. *Interdisciplinary Journal of Contemporary Research in Business*, 4(8), 788-805.

Reading, M., Baik, D., Beauchemin, M., Hickey, K. T., & Merrill, J. A. (2018). Factors influencing sustained engagement with ECG self-monitoring: perspectives from patients and health care providers. *Applied Clinical Informatics*, 9(04), 772-781.

Reno, R. R., Cialdini, R. B., & Kallgren, C. A. (1993). The transsituational influence of social norms. *Journal of Personality and Social Psychology*, 64(1), 104.

Ringle, C. M., & Sarstedt, M. (2016). Gain more insight from your PLS-SEM results: The importance-performance map analysis. *Industrial Management & Data systems*.

Roberts, R. C. (2003). Emotions: An essay in aid of moral psychology. *Cambridge University Press*.

Robinson, J. P., Shaver, P. R., & Wrightsman, L. S. (1999). Measures of political attitudes. *Academic Press*.

Rogers, A., Kovaleva, O., & Rumshisky, A. (2020). A primer in bertology: What we know about how bert works. *Transactions of the Association for Computational Linguistics*, 8, 842-866.

Rogers, C. R. (1962). The interpersonal relationship: The core of guidance. *Harvard Educational Review*.

Rose, S., Clark, M., Samouel, P., & Hair, N. (2012). Online customer experience in e-retailing: an empirical model of antecedents and outcomes. *Journal of Retailing*, 88(2), 308-322.

Rosenstone, S. J., Hansen, J. M., & Kinder, D. R. (1986). Measuring change in personal economic well-being. *Public Opinion Quarterly*, 50(2), 176-192.

Rossin, D., Ro, Y. K., Klein, B. D., & Guo, Y. M. (2009). The effects of flow on learning outcomes in an online information management cou. *Journal of Information Systems Education*, 20(1), 87-98.

Rutherford, A. (2011). ANOVA and ANCOVA: a GLM approach. *John Wiley & Sons*.

S.Y. Park, J.S. Song, H.D. Kim, K. Yamane, K.C. Son. (2008). "Effects of interior plantscapes on indoor environments and stress level of high school students" J. Jpn. Soc. Hortic. Sci., 77 (2008), pp. 447-454.

Saeed, K. A., & Abdinnour-Helm, S. (2008). Examining the effects of information system characteristics and perceived usefulness on post adoption usage of information systems. *Information & Management*, 45(6), 376-386.

Saeed, K. A., & Abdinnour-Helm, S. (2008). Examining the effects of information system characteristics and perceived usefulness on post adoption usage of information systems. *Information & Management*, 45(6), 376-386.

Sahin, I., & Thompson, A. (2007). Analysis of predictive factors that influence faculty members' technology adoption level. *Journal of Technology and Teacher Education*, 15(2), 167–190.

Sarstedt, M., Hair, J. F., Ringle, C. M., Thiele, K. O., & Gudergan, S. P. (2016). Estimation issues with PLS and CBSEM: Where the bias lies!. *Journal of Business Research*, 69(10), 3998-4010.

Sarstedt, M., Henseler, J., & Ringle, C. M. (2011). Multigroup analysis in partial least squares (PLS) path modeling: Alternative methods and empirical results. In Measurement and research methods in international marketing. *Emerald Group Publishing Limited*.

Saunders, M., Lewis, P., & Thornhill, A. (2019). Research methods for business students (8th ed.). Pearson Education.

Schepers, J. and Wetzels, M. "A Meta-analysis of the Technology Acceptance Model: Investigating Subjective Norm and Moderation Effects," *Information and Management* (44), 2007, pp. 90-103. 18

Scherer, R., Siddiq, F., & Tondeur, J. (2019). The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. *Computers & Education*, 128, 13-35.

Schlägel, C., & Sarstedt, M. (2016). Assessing the measurement invariance of the four-dimensional cultural intelligence scale across countries: A composite model approach. *European Management Journal*, 34(6), 633-649.

Schreiber, J. B., Nora, A., Stage, F. K., Barlow, E. A., & King, J. (2006). Reporting structural equation modeling and confirmatory factor analysis results: A review. *The Journal of Educational Research*, 99(6), 323-338.

Schumacker, R. E., & Lomax, R. G. (2004). A beginner's guide to structural equation modeling. *Psychology Press*.

Schuman, H., Presser, S., & Ludwig, J. (1981). Context effects on survey responses to questions about abortion. *Public Opinion Quarterly*, 45(2), 216-223.

Schunk, D. H. (1981). Modeling and attributional effects on children's achievement: A self-efficacy analysis. *Journal of Educational Psychology*, 73(1), 93.

Schwarz, A., & Chin, W. (2007). Looking forward: Toward an understanding of the nature and definition of IT acceptance. *Journal of the Association for Information Systems*, 8(4), 4.

Schwarz, N., & Wyer Jr, R. S. (1985). Effects of rank ordering stimuli on magnitude ratings of these and other stimuli. *Journal of Experimental Social Psychology*, 21(1), 30-46.

Schwarz, N., Hippler, H. J., Deutsch, B., & Strack, F. (1985). Response scales: Effects of category range on reported behavior and comparative judgments. *Public Opinion Quarterly*, 49(3), 388-395.

Seethamraju, R., Diatha, K. S., & Garg, S. (2018). Intention to use a mobile-based information technology solution for tuberculosis treatment monitoring–applying a UTAUT model. *Information Systems Frontiers*, 20(1), 163-181.

Selwyn, N. (2013). Distrusting educational technology: Critical questions for changing times. *Routledge*.

Setiasih, R. O., Setiawardani, W., & Yusron, E. (n.d.). *Applying the UTAUT Model to Understand Factors Affecting the Use of Learning Management System for Learning Pedagogical Education*.

Shafi, A. S., & Weerakkody, V. (2009, January). Understanding citizens' behavioural intention in the adoption of e-government services in the state of Qatar. In ECIS (Vol. 1, pp. 1618-1629).

Shareef, M. A., Baabdullah, A., Dutta, S., Kumar, V., & Dwivedi, Y. K. (2018a). Consumer adoption of mobile banking services: An empirical examination of factors according to adoption stages. *Journal of Retailing and Consumer Services*, 43, 54-67.

Shareef, M. A., Mukerji, B., Alryalat, M. A. A., Wright, A., & Dwivedi, Y. K. (2018b). Advertisements on Facebook: Identifying the persuasive elements in the development of positive attitudes in consumers. *Journal of Retailing and Consumer Services*, 43, 258-268.

Sharma, S. K., Mangla, S. K., Luthra, S., & Al-Salti, Z. (2018). Mobile wallet inhibitors: Developing a comprehensive theory using an integrated model. *Journal of Retailing and Consumer Services*, 45, 52-63.

Shaw, N., & Sergueeva, K. (2019). The non-monetary benefits of mobile commerce: Extending UTAUT2 with perceived value. *International Journal of Information Management*, 45, 44-55.

Sheppard, B. H., Hartwick, J., & Warshaw, P. R. (1988). The theory of reasoned action: A meta-analysis of past research with recommendations for modifications and future research. *Journal of Consumer Research*, 15(3), 325-343.

Shi, Y. L., Chen, W. Q., Wu, S. L., & Zhu, Y. G. (2017). Anthropogenic cycles of arsenic in mainland China: 1990–2010. *Environmental Science & Technology*, 51(3), 1670-1678.

Shiferaw, K. B., & Mehari, E. A. (2019). Modeling predictors of acceptance and use of electronic medical record system in a resource limited setting: using modified UTAUT model. *Informatics in Medicine Unlocked*, 17, 100182.

Shin, D. H. (2009). Towards an understanding of the consumer acceptance of mobile wallet. *Computers in Human Behavior*, 25(6), 1343-1354.

Simon, H. A. (1957). Models of man; social and rational.

Sinha, A., Kumar, P., Rana, N. P., Islam, R., & Dwivedi, Y. K. (2019). Impact of internet of things (IoT) in disaster management: a task-technology fit perspective. *Annals of Operations Research*, 283(1- 2), 759-794.

Sivertsen, G. (2017). Unique, but still best practice? The Research Excellence Framework (REF) from an international perspective. *Palgrave Communications*, 3(1), 1-6.

Slade, E. L., Williams, M. D., & Dwivedi, Y. K. (2014). Devising a research model to examine adoption of mobile payments: An extension of UTAUT2. *The Marketing Review*, 14(3), 310-335.

So, J. C., & Bolloju, N. (2005). Explaining the intentions to share and reuse knowledge in the context of IT service operations. *Journal of Knowledge Management*.

Subramanian, G.H. “A Replication of Perceived Usefulness and Perceived Ease of Use Measurement,” *Decision Sciences* (25: 5/6), 1994, pp. 863-874.

Sugar, W., Crawley, F., & Fine, B. (2004). Examining teachers' decisions to adopt new technology. *Journal of Educational Technology & Society*, 7(4), 201-213.

Suter, R., Miladinovic, D., Schölkopf, B., & Bauer, S. (2019, May). Robustly disentangled causal mechanisms: Validating deep representations for interventional robustness. In International Conference on Machine Learning (pp. 6056-6065). PMLR.

Szajna, B. (1996). “Empirical Evaluation of the Revised Technology Acceptance Model,” *Management Science* (42: 1), 1996, pp. 85-92.

Szajna, B. (1996). Empirical evaluation of the revised technology acceptance model. *Management Science*, 42(1), 85-92.

Taylor, S., and Todd, P. A. “Assessing IT Usage: The Role of Prior Experience,” *MIS Quarterly* (19:2), 1995a, pp. 561-570.

Tagoe, M. A., & Abakah, E. (2014). Determining Distance Education Students' Readiness for Mobile Learning at University of Ghana Using the Theory of Planned Behavior. *International Journal of Education and Development using Information and Communication Technology*, 10(1), 91-106.

Taherdoost, H. (2018). A review of technology acceptance and adoption models and theories. *Procedia Manufacturing*, 22, 960-967.

Tak, P., & Panwar, S. (2017). Using UTAUT 2 model to predict mobile app based shopping: evidences from India. *Journal of Indian Business Research*.

Tamilmani, K., Rana, N. P., & Dwivedi, Y. K. (2017). A systematic review of citations of UTAUT2 article and its usage trends. Paper presented at the Conference on e-Business, e-Services and e-Society.

Tamilmani, K., Rana, N. P., Prakasam, N., & Dwivedi, Y. K. (2019). The battle of Brain vs. Heart: A literature review and meta-analysis of "hedonic motivation" use in UTAUT2. *International Journal of Information Management*, 46, 222-235.

Tamres, L. K., Janicki, D., & Helgeson, V. S. (2002). Sex differences in coping behavior: A meta-analytic review and an examination of relative coping. *Personality and Social Psychology Review*, 6(1), 2–30. https://doi.org/10.1207/S15327957PSPR0601_1

Tan, M., & Teo, T. S. (2000). Factors influencing the adoption of Internet banking. *Journal of the Association for Information Systems*, 1(1), 5.

Tarhini, A., Hone, K., & Liu, X. (2015). A cross-cultural examination of the impact of social, facilitating conditions and performance expectancy on behavioral intention to use technology. *Educational Technology Research and Development*, 63(2), 221–239. https://doi.org/10.1007/s11423-014-9363-1

Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. *International Journal of Medical Education*, 2, 53.

Taylor, S., & Todd, P. (1995). Decomposition and crossover effects in the theory of planned behavior: A study of consumer adoption intentions. *International Journal of Research in Marketing*, 12(2), 137-155.

Taylor, S., and Todd, P. A. (1995). "Understanding Information Technology Usage: A Test of Competing Models," *Information Systems Research* (6:4), 1995b, pp. 144-176.

Teo, T. (2010). Development and validation of the E-learning Acceptance Measure (ElAM). *The Internet and Higher Education*, 13(3), 148-152.

Teo, T. (2011). Factors influencing teachers' intention to use technology: Model development and test. *Computers & Education*, 57(4), 2432-2440.

Teo, T., & Lee, C. B. (2010). Examining the efficacy of the theory of planned behavior (TPB) to understand pre-service teachers' intention to use technology.

Tey, T. C. Y., & Moses, P. (2018). UTAUT: Integrating achievement goals and learning styles for undergraduates' behavioural intention to use technology. *EAI Endorsed Transactions on e-Learning*, 5(17), 1-12.

Thomas, J., Utley, J., Hong, S. Y., Korkmaz, H., & Nugent, G. (2020). A Review of the Research. *Handbook of Research on STEM Education*.

Thompson, R. L., Higgins, C. A., and Howell, J. M. "Influence of Experience on Personal Computer Utilization: Testing a Conceptual Model," *Journal of Management Information Systems* (11:1), 1994, pp. 167-187.

Thompson, R. L., Higgins, C. A., and Howell, J. M. "Personal Computing: Toward a Conceptual Model of Utilization," *MIS Quarterly* (15:1), 1991, pp. 125-143.

Thomson, E., Hanson, T. L., & McLanahan, S. S. (1994). Family structure and child well-being: Economic resources vs. parental behaviors. *Social Forces*, 73(1), 221-242.

Thong, J. Y., Hong, S. J., & Tam, K. Y. (2006). The effects of post-adoption beliefs on the expectation-confirmation model for information technology continuance. *International Journal of Human-Computer Studies*, 64(9), 799-810.

Thurstone, L. L. (1928). Attitudes can be measured. American journal of Sociology, 33(4), 529-554.

Tibenderana, P., Ogao, P., Ikoja-Odongo, J., & Wokadala, J. (2010). Measuring levels of end-users' acceptance and use of hybrid library services. *International Journal of Education and Development using ICT*, 6(2), 33-54.

Tobin, J., Fong, R., Ray, A., Schneider, J., Zaremba, W., & Abbeel, P. (2017, September). *Domain randomization for transferring deep neural networks from simulation to the real world.* In 2017 IEEE/RSJ international conference on intelligent robots and systems (IROS) (pp. 23-30). IEEE.

Tourangeau, R., & Rasinski, K. A. (1988). Cognitive processes underlying context effects in attitude measurement. *Psychological Bulletin*, 103(3), 299.

Triandis, H. C. (1971). Attitude and Attitude Change. *Wiley Foundations of Social Psychology Series*.

Triandis, H. C. (1980). Reflections on trends in cross-cultural research. *Journal of Cross-Cultural Psychology*, 11(1), 35-58.

Triandis, H. C. Interpersonal Behavior, Brooke/ Cole, Monterey, CA, 1977. Vallerand, R. J. "Toward a Hierarchical Model of Intrinsic and Extrinsic Motivation," in Advances in Experimental Social Psychology (29), M. Zanna (ed.), Academic Press, New York, 1997, pp. 271-360.

Twigg, J. (2003). The Human Factor in Early Warnings: Risk Perception and Appropriate Communications. In: Zschau, J., Küppers, A. (eds) Early Warning Systems for Natural Disaster Reduction. *Springer*, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-55903-7_4

Uysal, M. and Hagan, L. A. R. (1993) "Motivation of Pleasure Travel and Tourism" *Encyclopedia of Hospitality and Tourism* 798-810.

Vallerand, R. J. (1997). Toward a hierarchical model of intrinsic and extrinsic motivation. In Advances in experimental social psychology (Vol. 29, pp. 271-360). *Academic Press*.

Vallerand, R. J., & Losier, G. F. (1999). An integrative analysis of intrinsic and extrinsic motivation in sport. *Journal of Applied Sport Psychology*, 11(1), 142-169.

Van der Heijden, H. (2004). User acceptance of hedonic information systems. *MIS Quarterly*, 695-704.

Van Maanen, J., and Barley, S.R. (1985). "Cultural Organization: Fragments of a Theory," in Organizational Culture, P.J. Frost, L.F. Moore, M.R. Louis, C.C. Lundberg, and J. Martin (eds.), *Sage Publications*, London, 1985, pp. 31-54.

Vecchio, R. P. (2002). Leadership and gender advantage. *The Leadership Quarterly*, 13(6), 643–671. https://doi.org/10.1016/S1048-9843(02)00156-X

Veeramootoo, N., Nunkoo, R., & Dwivedi, Y. K. (2018). What determines success of an egovernment service? Validation of an integrative model of e-filing continuance usage. *Government Information Quarterly*, 35(2), 161-174

Venkatesh, V. (1999). "Creating Favorable User Perceptions: Exploring the Role of Intrinsic Motivation," *MIS Quarterly* (23:2), 1999, pp. 239-260.

Venkatesh, V. "Determinants of Perceived Ease of Use: Integrating Perceived Behavioral Control, Computer Anxiety and Enjoyment into the Technology Acceptance Model," Information Systems Research (11:4), 2000, pp. 342-365.

Venkatesh, V., & Morris, M. G. (2000). Why don't men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behavior. *MIS Quarterly*, 115-139.

Venkatesh, V., and Davis, F. D. (2000). "A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies," *Management Science* (46:2), 2000, pp. 186-204.

Venkatesh, V., and Morris, M. G. "Why Don't Men Ever Stop to Ask For Directions? Gender, Social Influence, and Their Role in Technology Acceptance and Usage Behavior," *MIS Quarterly* (24:1), 2000, pp. 115-139.

Venkatesh, V., Brown, S. A., & Bala, H. (2013). Bridging the qualitative-quantitative divide: Guidelines for conducting mixed methods research in information systems. *MIS Quarterly*, 21-54.

Venkatesh, V., Brown, S. A., Maruping, L. M., & Bala, H. (2008). Predicting different conceptualizations of system use: The competing roles of behavioral intention, facilitating conditions, and behavioral expectation. *MIS Quarterly*, 483-502.

Venkatesh, V., Morris, M. G., and Ackerman, P. L. (2000). "A Longitudinal Field Investigation of Gender Differences in Individual Technology Adoption Decision Making Processes," *Organizational Behavior and Human Decision Processes* (83:1), 2000, pp. 33-60. 19 20

Venkatesh, V., Morris, M., Davis, G.B., and Davis, F.D. (2003). "User Acceptance of Information Technology: Toward a Unified View," *MIS Quarterly* (27:3), 2003, pp. 425-78.

Venkatesh, V., Speier, C., & Morris, M. G. (2002). User acceptance enablers in individual decision making about technology: Toward an integrated model. *Decision Sciences*, 33(2), 297-316.

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 157-178.

Venkatesh, V., Thong, J. Y., & Xu, X. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. *Journal of The Association for Information Systems*, 17(5), 328-376.

Voyer, D., & Voyer, S. D. (2014). Gender differences in scholastic achievement: A meta-analysis. *Psychological Bulletin*, 140(4), 1174–1204. https://doi.org/10.1037/a0036620

Wagner, C. S., & Leydesdorff, L. (2005). Network structure, self-organization, and the growth of international collaboration in science. *Research Policy*, 34(10), 1608-1618.

Wagner, P. (2008). Modernity as experience and interpretation. Polity.

Waheed, M., & Jam, F. A. (2010). Teacher's intention to accept online education: Extended TAM model. *Interdisciplinary Journal of Contemporary Research in Business*, 2(5), 330-344.

Walter, Z., and Lopez, M.S. "Physician Acceptance of Information Technologies: Role of Perceived Threat to Professional Autonomy," *Decision Support Systems* (46), 2008, pp. 206-215.

Walter, Z., and Lopez, M.S. "Physician Acceptance of Information Technologies: Role of Perceived Threat to Professional Autonomy," *Decision Support Systems* (46), 2008, pp. 206-215.

Waltman, L. (2016). A review of the literature on citation impact indicators. *Journal of Informetrics*, 10(2), 365-391.

Wan, L., Xie, S., & Shu, A. (2020). Toward an understanding of university students' continued intention to use MOOCs: When UTAUT model meets TTF model. Sage Open, 10(3), 2158244020941858.

Wang, J., Berzins, K., Hicks, D., Melkers, J., Xiao, F., & Pinheiro, D. (2012). A boosted-trees method for name disambiguation. *Scientometrics*, 93(2), 391-411.

Wang, Z., Tchernev, J. M., & Solloway, T. (2012). A dynamic longitudinal examination of social media use, needs, and gratifications among college students. *Computers in Human Behavior*, 28(5), 1829-1839.

Warshaw, P. R. "A New Model for Predicting Behavioral Intentions: An Alternative to Fishbein," *Journal of Marketing Research* (17:2), 1980, pp. 153-172.

Warwick, D. P., & Lininger, C. A. (1975). The sample survey: Theory and practice. McGraw-Hill.

Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: the PANAS scales. *Journal of Personality and Social Psychology*, 54(6), 1063.

Wedell, D. H., & Parducci, A. (1988). The category effect in social judgment: Experimental ratings of happiness. *Journal of Personality and Social Psychology*, 55(3), 341.

Wedell, D. H., Parducci, A., & Geiselman, R. E. (1987). A formal analysis of ratings of physical attractiveness: Successive contrast and simultaneous assimilation. *Journal of Experimental Social Psychology*, 23(3), 230-249.

Wedell, D. H., Parducci, A., & Lane, M. (1990). Reducing the dependence of clinical judgment on the immediate context: Effects of number of categories and type of anchors. *Journal of Personality and Social Psychology*, 58(2), 319.

Wheaton, B., Muthen, B., Alwin, D. F., & Summers, G. F. (1977). Assessing reliability and stability in panel models. *Sociological Methodology*, 8, 84-136.

Whetten, D. A. (2009). An examination of the interface between context and theory applied to the study of Chinese organizations. *Management and Organization Review*, 5(1), 29-56.

Williams, M. D., Rana, N. P., & Dwivedi, Y. K. (2015). The unified theory of acceptance and use of technology (UTAUT): a literature review. *Journal of Enterprise Information Management*, 28(3), 443.

Wilsdon, J., Allen, L., Belfiore, E., Campbell, P., Curry, S., Hill, S., ... & Johnson, B. (2015). The metric tide. *Report of the independent review of the role of metrics in research assessment and management*.

Wixom, B.H., and Todd, P.A. "A Theoretical Integration of User Satisfaction and Technology Acceptance," *Information Systems Research* (16:1), 2005, pp. 85-102.

Wu, B., & Chen, X. (2017). Continuance intention to use MOOCs: Integrating the technology acceptance model (TAM) and task technology fit (TTF) model. *Computers in Human Behavior*, 67, 221-232.

Wu, B., Altrock, P. M., Wang, L., & Traulsen, A. (2010). Universality of weak selection. *Physical Review* E, 82(4), 046106.

Xia, F., Yang, L. T., Wang, L., & Vinel, A. (2012). Internet of things. *International Journal of Communication Systems*, 25(9), 1101.

Yilmaz, K. (2013). Comparison of quantitative and qualitative research traditions: Epistemological, theoretical, and methodological differences. *European Journal of Education*, 48(2), 311-325.

Yuniarty, Lohannes, Lohansen, & Hartono, F. (2024). Optimizing Learning Management System Using UTAUT Model: Environment, Compatibility, Material Content, and Interactivity for Enhanced Usability. *Multidisciplinary Science Journal*, *7*(3), 2025111. https://doi.org/10.31893/multiscience.2025111

Yoo, Y., Boland Jr, R. J., Lyytinen, K., & Majchrzak, A. (2012). Organizing for innovation in the digitized world. *Organization Science*, 23(5), 1398-1408.

Zaman, B. U. I. (2024). *Transforming Education Through AI Benefits Risks and Ethical Considerations*. https://doi.org/10.20944/preprints202407.0859.v1

Zhao, Y., & Frank, K. A. (2003). Factors affecting technology uses in schools: An ecological perspective. *American Educational Research Journal*, 40(4), 807–840. https://doi.org/10.3102/00028312040004807

Zhou, M. (2016). Chinese university students' acceptance of MOOCs: A self-determination perspective. *Computers & Education*, 92, 194-203.

Zhou, T. (2013). An empirical examination of continuance intention of mobile payment services. *Decision Support Systems*, 54(2), 1085-1091.

Zhu, K., & Kraemer, K. L. (2005). Post-adoption variations in usage and value of e-business by organizations: cross-country evidence from the retail industry. *Information Systems Research*, 16(1), 61-84.

Appendices and Annexures

Survey Instrument

Dear Sir/Madam,

This is a questionnaire which tries to measure the drivers and barriers for educators in adopting education technology in their classroom pedagogy. Education Technology can be any form of technology that can be used in your day-to-day teaching and other allied administrative tasks. Technologies here could include any of these but not restricted to computer, internet, TV, Music, Multimedia, projector, smart boards, whiteboards, any specialized software such as Excel, PowerPoint, Word, R, SPSS, Python, Minecraft, Sway or any Learning Management System such as Canvas etc. You may also use some online tools such as Google Forms, Google Drive, Google Classroom etc. Education technology here also can include simulation software used to teach some courses such as Business Strategy.

This survey is a part of my Ph.D. thesis and your responses will be used strictly for academic research.

As an expert, I request you to spare some time to review these survey items for content validity. Those questions which you feel are not necessary or need to be modified can be highlighted in red, with your remarks.

I would be highly obliged.

Thanks in advance.

Regards

Rajesh Dorbala

Basic Details:

Name:

University:

Age:

Gender:

Experience:

Faculty: What is your (main) faculty affiliation?

Position: What is your academic position?

University Type: (A) Central (B) State

Please Mark your preferences as per the following parameters:

Strongly Disagree: 1

Disagree: 2

Neutral: 3

Agree: 4

Strongly Agree: 5

Performance Expectancy

Statement	1	2	3	4	5
I find Education Technology useful within my teaching assignments					
Using Education Technology enhances my effectiveness as a teacher.					
Through using Education Technology, I increase my chances of receiving good student feedback					
I find Education Technology useful in my day-to-day activities.					
Using Education Technology increases my chances of achieving things that are important to me.					
Using technology in classroom helps me accomplish things more quickly					
Using technology in my day-to-day classroom activities increases my productivity					

Effort Expectancy

Statement	1	2	3	4	5
I find Education Technology clear and understandable					
It is easy for me to become skilful at using Education Technology					
I find Education Technology easy to use					
Learning to work with Education Technology is easy					
Learning to use Education Technology products is easy for me.					

Social influence

Statement	1	2	3	4	5
My colleagues think that I should use Education Technology more innovatively					
Colleagues, who are important to me, think that I should use Education Technology					
The educational council of my programme supports the use of Education Technology					
In general, the university supports the use of Education Technology					
In general, the faculty supports the use of Education Technology					
The chairman of my educational council thinks that I should use Education Technology					
People who influence my behavior think that I should use Technology in my classroom					

Perceived Enjoyment

Statement	1	2	3	4	5
Using education technology provides me with a lot of enjoyment					
I enjoy using education technology					
The process of using education technology is enjoyable					
While using education technology, I experience pleasure					
Overall, I believe education technology is playful					
It would be fun to use education technology					
I don’t get bored while using education technology					
Education technology makes my leisure time more fun					

Facilitating conditions

Statement	1	2	3	4	5
I have the resources necessary to use Education Technology					
Education Technology is compatible with the way I teach					
A specific person is available for assistance with difficulties when using Education Technology					
I have the knowledge necessary to use Education Technology					
I feel that I can make informed decisions about which tools/resources to use within Education Technology					
I feel that I can fully take advantage of Education Technology thanks to the resources within Education Technology					
I have looked for tools outside of Education Technology so that I can further innovate with my teaching through technology					

Behavior Intention

Statement	1	2	3	4	5
I intend to use technology in my classroom in the future					
I will always try to use Education Technology in my day-to-day activities in my classroom					
I plan to use education technology frequently					
When I hear about a new technology, I often find an excuse to use it					
Among my peers, I am the first one to use any new technology					
Assuming that I have access to Education Technology, I intend to use it.					

Amount of Use

Statement	1	2	3	4	5
I spend several hours per day using virtual reality environments in teaching					
I spend several hours per day using digital databases					
I spend several hours per day using digital libraries					
I spend several hours per day using online media repositories					
I spend several hours per day using online survey tools					
I spend several hours per day using video and sound recording technologies for preparing my lectures					
I spend several hours per day using data analysis software					
I spend several hours per day using word processing technologies such as MS Word					
I spend several hours per day using video conferencing software to interact with students					
I spend several hours per day using quiz creation software and tools to make my lessons engaging and interactive					
I spend several hours per day using collaboration tools such as Google classroom					
I spend several hours per day using simulation games to make my lessons engaging and practical					
I spend several hours per day using computer assisted design software					
I spend several hours per day using visualization tools such as Tableau and Excel etc.					

I spend several hours per day using drawing and painting technologies to make my lessons realistic					
I spend several hours per day using animation technologies such as Powtoon and Scratch to make my lessons visually appealing					
I spend several hours per day using Multimedia composition technologies such as Adobe Spark, Movie Maker etc. to add zing to my lessons					

Variety of Use

Statement	**1**	**2**	**3**	**4**	**5**
I often use virtual reality environments in teaching					
I often use digital databases					
I often use digital libraries					
I often use online media repositories					
I often use online survey tools					
I often use video and sound recording technologies for preparing my lectures					
I often use data analysis software					
I often use word processing technologies such as MS Word					
I often use video conferencing software to interact with students					
I often use quiz creation software and tools to make my lessons engaging and interactive					
I often use collaboration tools such as Google classroom					
I often use simulation games to make my lessons engaging and practical					
I often use computer-assisted design software					
I often use visualization tools such as Tableau and Excel etc.					
I often use drawing and painting technologies to make my lessons realistic					
I often use animation technologies such as Powtoon and Scratch to make my lessons visually appealing					
I often use Multimedia composition technologies such as Adobe Spark, Movie Maker etc. to add zing to my lessons					

Type of Use

Statement	**1**	**2**	**3**	**4**	**5**
I often use technology for Inquiry					
I often use Education Technology for communication					
I often use technology for construction and problem solving					
I often use technology for knowledge representation					
I often use technology for assessment					
I often use technology for classroom efficiency					
I often use technology for classroom management					
I often use technology for classroom response system					
I often use technology for collaboration tools					
I often use technology for curriculum platforms					
I often use technology for grading and attendance					
I often use technology for lesson planning					
I often use technology for professional learning					
I often use technology for presentation tools					
I often use technology for special education					