# Factors Influencing Teachers' Use of Digital Learning Resources in Dakshina Kannada, India: A UTAUT2 Analysis

**Raghavendra[1*], Suvarni[2], Deeksha[3]**

[1]Faculty of Commerce, University Evening College, Mangaluru, India

ORCID ID: 0000-0002-2130-2476;

Email ID: dr.raghavendra23@gmail.com

[2]Assistant Professor in Commerce, Sri Bhuvanendra College Karkala, India

ORCID: 0009-0009-2593-8867

Email ID: suvarnasuvarni@gmail.com

[3]Lecturer In Commerce, Shree Devi College Ballalbagh Mangalore, India

ORCID: 0009-0004-0014-1468

Email ID: deekshasuvarna25.1995@gmail.com

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**Raghavendra[1*], Suvarni[2], Deeksha[3]**

[1]Faculty of Commerce, University Evening College, Mangaluru, India

ORCID ID: 0000-0002-2130-2476;

Email ID: dr.raghavendra23@gmail.com

[2]Assistant Professor in Commerce, Sri Bhuvanendra College Karkala, India

ORCID: 0009-0009-2593-8867

Email ID: suvarnasuvarni@gmail.com

[3]Lecturer In Commerce, Shree Devi College Ballalbagh Mangalore, India

ORCID: 0009-0004-0014-1468

Email ID: deekshasuvarna25.1995@gmail.com

## ABSTRACT

***Purpose:*** *This study used the UTAUT2 (Unified Theory of Acceptance and Use of Technology 2) paradigm to investigate the factors influencing teachers' adoption of Digital Learning Resources (DLR). In addition to examining variations by gender, frequency of technology use, and academic field, this study assesses the influence of Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), Price Value (PV), and Habit (HB) on behavioural intention (BI) and use behaviour (UB).*

***Design/methodology/approach:*** *Data were gathered from 502 teachers in nine taluks in Dakshina Kannada, India using a quantitative study approach and stratified random sampling. Google Forms and offline surveys were used to collect data, and structural equation modelling (SEM) was used for analysis. Group differences were also investigated using one-way analysis of variance (ANOVA) and independent sample t-tests.*

***Findings:*** *The findings showed that teachers' BIs were highly influenced by PV, HM, SI, PE, and EE. Use behaviour is greatly influenced by behavioural aims and facilitating circumstances. FC did not affect BI, and HB had no discernible impact on BI or UB. Gender-based BI did not differ significantly according to the group analysis; however, the frequency of technology use and field of study did differ significantly.*

***Practical implications:*** *This study highlights the need for customised training, improved digital infrastructure, and targeted professional development to enhance the integration of digital tools in education.*

***Originality/value:*** *This study provides empirical insights into digital adoption patterns among teachers and offers valuable guidance to policymakers and teachers aiming to enhance technology-driven learning environments.*

***Type of the paper:*** *Original Article*

**Keywords:** Digital Learning Resources (DLR), UTAUT2, Technology Adoption, Teachers, Structural Equation Modelling (SEM)

## 1. INTRODUCTION:

Teachers play a role in influence students' intellectual and social growth. They teach learners at various educational levels, including elementary, middle, and high schools. NEP 2020 highlights the importance of incorporating technology in classrooms, which enriches learning experiences through platforms such as Diksha, SWAYAM, and Smart Classes. Research indicates that digital training programs assist teachers in adapting to changing educational demands, thereby enhancing their proficiency in utilising online resources (Avci, 2022) [1]. Examining how teachers employ digital resources is vital for boosting student performance, refining curriculum designs, and promoting effective teaching methods, thereby encouraging innovation and inclusivity in education. The growing dependence on digital learning tools has notably altered educational practices in India. The change to e-learning has improved accessibility and flexibility, enabling teachers to reach a wider audience and engage students more effectively (Fauzi et al., 2023) [2]. Studies emphasise the significance of ICT (Information and Communication Technology) in addressing real-world challenges and creating interactive and personalised learning settings that can enhance educational results (Villasmil, 2024) [3]. However, obstacles such as a shortage of technological infrastructure and different levels of digital adoption among teachers impede this transition (Blichfeldt et al., 2019) [4]. Research suggests that incorporating blended learning, which merges traditional and online approaches, can enrich educational experience (Bilanová, 2019) [5]. Additionally, Teachers are encouraged to use multimedia resources and interactive tools to boost engagement (Sudimantara 2023) [6]. Ongoing professional development is crucial for effectively utilising these digital tools, ensuring that teachers can fully harness the advantages of Digital Learning Resources (hereafter called DLR) (Kamanasa et al., 2024) [7]. Aithal (2019) [8] recommended that teachers integrate Information, Communication, and Computation Technology (ICCT) throughout various teaching and learning processes to improve educational outcomes and create more student-centric, efficient, and personalised learning environments. The Dakshina Kannada district in Karnataka, India, has become a key centre for education and technology, particularly in promoting entrepreneurship through incubation centres within management institutes. Despite the availability of colleges offering entrepreneurship education, research reveals a gap between academic training and actual entrepreneurial success in the area, underscoring the need for enhanced practical engagement and support systems (Panakaje, 2024) [9]. Moreover, the incorporation of technology into education is apparent through various efforts aimed at enhancing community health awareness and practices, such as ensuring medication adherence among older adults (Udupa 2023) [10]. Educational institutions in the region are increasingly emphasising the connection between theoretical understanding and practical execution, thereby aiding the overall growth of the local economy and community welfare (Secundo et al. 2021) [11]. This collaboration between education and technology is important to bring up an innovative culture and entrepreneurship in Dakshina Kannada. Despite the increasing focus on DLR and the increasing technology integration in Indian education, particularly in the Dakshina Kannada District, there is still a dearth of research on the factors impacting teachers' acceptance and usage of DLR in the region. Study uses the UTAUT2 (Unified Theory of Acceptance and Use of Technology 2) model which aims to forecast the user adoption of technology in consumer settings more accurately.

UTAUT2 includes Hedonic Motivation (hereafter called HM), which describes the pleasure or happiness gained from utilising the technology. (Tavares & Oliveira, 2016) [12], Price Value (hereafter called PV), perceived cost-benefit ratio, in which users weigh the advantages of the technology against financial expenses (Addy et al., 2022) [13], and alongside the original constructs of Habit (hereafter called HB), which measures how individuals often accomplish behaviours owing to learning (Kułak et al., 2019) [14]. Performance Expectancy (hereafter called PE), which measures how much using a technology is perceived to improve performance of job; Effort Expectancy (hereafter called EE), which measures how easy it is perceived to use; Social Influence (hereafter called SI), which measures how much people believe that important others think they should use the new system; and Facilitating Condition (hereafter called FC), which measures the resources and support available to use the technology (Mookerjee, 2023; Pasaribu, 2022) [15, 16]. This model's resilience in understanding technology adoption behaviors is evident in its widespread application across various domains, including mobile banking, e-learning, and health technologies, where Behavioral Intention (hereafter called BI) and Use Behavior (hereafter called UB) play a crucial role.

Research indicates that UTAUT2 effectively captures the complexities of user behaviour, particularly in consumer settings where emotional and habitual factors play significant roles (Liu et al., 2022) [17]. Studies have shown that the model's constructs can vary in significance depending on the context, highlighting the need for adaptations to fit specific technological environments (Çera et al., 2021) [18]. Overall, UTAUT2 is a valuable tool for practitioners and academics because it provides a thorough framework for comprehending the complex nature of adoption of technology.

## 2. OBJECTIVES:

[1] To examine the key factors influencing teachers' adoption and use of DLR
[2] To analyse the impact of demographic factors on teachers' adoption and use of DLR.

## 3. RESEARCH HYPOTHESES:

### 3.1 Primary Hypotheses

**H1:** PE has a significant influence on BI to use DLR.
**H2:** EE has a significant influence on BI to use DLR.
**H3:** SI has a significant influence on BI to use DLR.
**H4:** HM has a significant influence on BI to use DLR.
**H5:** PV has a significant influence on BI to use DLR.
**H6:** HB has a significant influence on BI when using DLR.
**H7:** HB has a significant influence on the UB of DLR.
**H8:** FC has a significant influence on BI to use DLR.
**H9:** FC has a significant influence on the UB of DLR.
**H10:** BI has a significant influence on the UB of DLR.

### 3.2 Group Difference Hypotheses

**H11a:** There is a significant difference in the BI to use the DLR between male and female teachers.
**H11b:** BI to use DLR differs significantly based on teachers' frequency of technology use.
**H11c:** BI to use DLR differs significantly among teachers from different fields of study.

## 4. REVIEW OF LITERATURE:

This study reviews the UTAUT, UTAUT2, and TAM models to analyse research on teachers' adoption of educational technology. As shown in Table 1, the reviewed research examined important adoption-influencing aspects.

**Table 1:** Review of literature

| Sl. No. | Field of Study | Focus of the Research | Key Findings | Authors |
|---|---|---|---|---|
| 1 | Education Technology | Teachers' adoption of ICT in higher secondary schools. | The results show that a variety of factors, such as SI, accommodating surroundings and EE had a good effect on how teachers utilise ICT. Additionally, the association between the predictors and ICT use is mediated by behavioural goals. | (Shah et al., 2021) [19] |
| 2 | Education, e-learning | Immersion virtual reality (iVR) usage by pre-service primary teachers in Spain through UTAUT2 | The findings demonstrate how iVR is regarded as enjoyable, useful, and simple to use; the highest scores were given to HM, PE, and EE. However, PV and HB received the lowest scores, suggesting that prior usage patterns and financial considerations 3had little influence on students' adoption of technology. | (Rodríguez-Gil, 2024) [20] |
| 3 | Technology adoption in education | Adoption of the Merdeka Mengajar app using UTAUT2 | Although HB and enabling circumstances have little direct impact on use behaviour, PV, | (Aminah et al., 2024) [21] |

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| | | | hedonic incentive, SI, PE, and EE all had a major influence on BI. | |
| **4** | Education Technology | Teachers' plans to employ an expanded UTAUT2 paradigm to implement VR in the classroom | The findings indicate that performance expectation, EE, SI, conducive environments, and hedonic incentive all have a major effect on Teacher's intentions to keep utilising VR technology in the classroom. However, HB does not promote long-term use. Enhancing VR training, creating a welcoming environment for adoption, and increasing engagement are more ways to encourage sustained use. | (Du & Liang, 2024) [22] |
| **5** | Educational artificial intelligence (AIEd) | Teachers' acceptance of AIEd (Educational artificial intelligence) using UTAUT2 | The findings indicate that a variety of factors, such as HM, SI, enabling conditions, PE, EE, and intention to use AIEd, affect Teacher's acceptance of AIEd. Age, gender, and teaching style all have an impact on adoption, even if constructivist pedagogical approaches show a positive link with AIEd acceptability. | (Cabero-Almenara et al., 2024) [23] |
| **6** | Technology acceptance in education | Learning Management Systems (LMS) usage by Teachers'. | The findings indicate that hedonic incentive and favourable circumstances significantly predict BI to utilise Moodle. Nevertheless, there is no appreciable impact from HB, SI, PE, or EE. The UTAUT2. | (Raman & Don, 2013) [24] |
| **7** | Education, technology integration | Acceptance of mobile technology by educators for creative instruction using UTAUT2 | The general level of acceptance for mobile technologies is high. Hedonic incentive, HB, and effort anticipation all have a big impact on BI. PV, FC, SI, and PE did not exhibit any meaningful correlations. | (Ismail et al., 2022) [25] |
| **8** | Educational Technology | UTAUT2 factors' ability to predict teachers' intentions to employ digital teaching resources | The findings indicate that HM, PE, and HB all strongly predict teachers' BI to use digital instructional resources. Additionally, BI and HB predict use behaviour. 81% of the variable in BI may be attributed to extrinsic causes, whereas 67% of the difference in use behaviour can be accredited to exogenous factors plus BI. | (Avci, 2022) [1] |
| **9** | Chemistry education, educational technology | Using an expanded UTAUT model, factors affecting secondary school chemistry instructors' | The findings indicate that attitude towards utilising instructional software predicts usage behaviour more accurately than BI. The BI of current users is significantly influenced by facilitating settings. | (Chroustová et al., 2022) [26] |

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|---|---|---|---|---|
| | | adoption of instructional software | For non-planning users, PE, SI, and individual IT innovation are strong predictors of BI. | |
| **10** | Educational Technology, MOOCs | Factors impacting Teachers' adoption and utilisation of MOOCs through the expanded UTAUT2 model | The findings indicate that economic value, enabling variables, SI, and PE have an effect on Teachers BI to use MOOCs. Additionally, BI and favourable conditions have an impact on MOOC uptake. However, adoption is unaffected by hedonic drive or effort expectation. | (Tseng et al., 2022) [27] |
| **11** | ICT in Education | Effects of teachers' perceived infrastructure and self-efficacy on ICT usability | The findings demonstrate that both self-efficacy and ICT infrastructure strongly predict teachers' capacity to employ ICT in pedagogy. Infrastructure has less of an impact than self-efficacy, despite the fact that both elements are effective predictors. These findings align with the UTAUT paradigm, which holds that self-efficacy extends BI and infrastructure matching conducive conditions. | (Kundu et al., 2021) [28] |
| **12** | Information Systems in Higher Education | Faculty usage of learning management systems (LMS) utilising the UTAUT2 paradigm | The results indicate that SI, learning value, hedonic incentive, and HB all have an impact on faculty members' intentions to use LMS. | (Zwain & Haboobi, 2019) [29] |
| **13** | Information Systems, Education, Technology Adoption | Analyse how Augmented Reality (AR) technology is used in classrooms. | The results demonstrate that task-technology fit, PE, EE, SI, conducive environments, and HM all had a favourable impact on BI's usage of augmented reality (AR) in education. However, PV isn't that important. | (Faqih & Mousa Jaradat, 2021) [30] |
| **14** | Education, Technology Adoption, Learning Management Systems (LMS) | Analyse the variables affecting pre-service teachers' intentions to adopt learning management systems (LMS). | The findings display that SI and attitude have a considerable effect on BI's usage of LMS, while conducive environments had no effect. Additionally, SI, PE, and EE all affect attitude, but facilitating circumstances have little effect. The research model may account for 43% of the variation in BI to utilise LMS. | (Buabeng-Andoh & Baah, 2020) [31] |
| **15** | Education, Technology Adoption, UTAUT Model | Examine the elements affecting the adoption of technology by English teachers from Chinese ethnic minorities. | The results show that SI, PE, and the perceived significance of technology-related policies have a substantial impact on ethnic minority English instructors' intention to use technology. However, there is no discernible impact from enabling conditions or | (Huang, Teo, & Zhao, 2023) [32] |

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| | | | effort expectations. Furthermore, attitudes towards technology-related policies influenced by perceived cultural value. | |
| **16** | DLR and Technology Acceptance | A meta-analysis of the variables affecting the utilisation of online learning resources | Subjective norm, self-efficacy, and content quality all had a significant influence on use behaviour and intention, with use intention being more substantially affected. | (Bai & Jiang, 2022) [33] |
| **17** | Mobile Learning and Technology Acceptance | Using the UTAUT paradigm, students' usage of mobile learning applications in higher education | Students' use of mobile learning applications and the benefits of mobile learning initiatives are influenced by a number of significant factors, including perceived compatibility, perceived awareness and perceived efficacy, perceived security, and perceived resource availability. | (Almaiah et al., 2019) [34] |
| **18** | Web-Based E-Learning and Technology Acceptance | Factors affecting junior high education Using online e-learning for in-service training among teachers | Promotion of Internet Use Self-efficacy positively affects BIs in two ways: perceived utility and perceived ease of usage. Because of their perceived simplicity of use, BIs are negatively impacted by computer anxiety. Perceived utility and usage motivation are the two primary determinants of acceptance. | (Chen & Tseng, 2012) [35] |

***Source: Author's work***

## 5. VARIABLES INFLUENCING BI AND UB:

An overview of the major factors found in the literature that affect BI and use behaviour in teachers' use of educational technology is presented in Table 2. It emphasises each variable's function in the evaluated studies, the quantity of studies that looked at it, and whether or not it had a positive or negative impact.

**Table 2:** Summary of Variables Influencing BI and UB – Insights from Literature Review

| Variable | Role in Studies | Number of Studies Used | Positive Influence | Negative Influence |
|---|---|---|---|---|
| **BI** | Mediating → UB | 17 | 17 | 0 |
| **PE** | Independent → BI | 14 | 14 | 0 |
| **SI** | Independent → BI | 13 | 13 | 0 |
| **EE** | Independent → BI | 12 | 9 | 3 |
| **FC** | Independent → BI & UB | 11 | 7 | 4 |
| **HM** | Independent → BI | 10 | 7 | 3 |
| **HB** | Independent → BI & UB | 8 | 6 | 2 |
| **PV** | Independent → BI | 7 | 5 | 2 |
| **Attitude Toward Technology** | Independent, Mediating → BI | 6 | 6 | 0 |
| **Self-Efficacy** | Independent → BI | 5 | 5 | 0 |
| **Learning Value** | Independent → BI | 4 | 4 | 0 |

| | | | | |
|---|---|---|---|---|
| **ICT Infrastructure** | Independent → BI | 4 | 4 | 0 |
| **Task-Technology Fit** | Independent → BI | 3 | 3 | 0 |
| **Technology-Related Policy Importance** | Independent → BI | 3 | 3 | 0 |
| **Personal Innovativeness in IT** | Independent → BI | 3 | 3 | 0 |
| **Perceived Cultural Value** | Independent, Moderating → BI | 3 | 3 | 0 |
| **UB** | Dependent Variable | 16 | NA | NA |

***Source: Author's work***

## 6. KEY GROUPING VARIABLES IN TECHNOLOGY ADOPTION STUDIES:

Beyond's fundamental ideas of UTAUT2, several factors affect teachers' acceptance of DLR. However, several demographics, technology-related, and contextual factors also influence teachers' BI and use behaviour. These variables were used as grouping factors in comparative analyses, moderators, and control variables. The main grouping variables utilised in earlier studies are compiled in Table 3, along with the number of studies that considered each component.

**Table 3:** Categorization of Grouping Variables and Their Influence on Technology Adoption

| Category | Grouping Variable | Number of Studies Used each variable |
|---|---|---|
| **Demographic Variables** | Gender (Male vs. Female) | 2 |
| | Age | 1 |
| | Education Level | 2 |
| | Teaching Experience | 1 |
| | Ethnic Background | 1 |
| **Technology-Related Variables** | Prior Experience with Technology | 1 |
| | Frequency of Technology Use | 1 |
| | Technology Availability or Access | 1 |
| | Device Used | 1 |
| **Contextual Variables** | Institution Type | 1 |
| | Region or Country | 1 |
| | Teaching Modality | 1 |
| | Field of Study or Subject Area | 1 |

***Source: Author's work***

## 7. THEORETICAL FOUNDATION:

The UTAUT2 model is a revolutionary paradigm for understanding consumers technology adoption. It expands on its predecessor, UTAUT, by including additional components, such as HM, PV, and HB, all of which have a greater influence on BIs. While UTAUT was originally developed to explain technology adoption in workplaces where usage was obligatory, UTAUT2 is more appropriate for optional contexts, such as consumer technology and education (Albastaki et al., 2024; Wang et al., 2021). [36, 37]. The enjoyment people derive from utilising technology is known as HM, which raises the possibility that people may adopt engaging digital technologies (Lin et al., 2022). [38]. PV assesses whether customers think that technology is worth the money, which is a crucial consideration in education, particularly in environments with constrained funding (Liu et al., 2022). [39]. As HB exemplifies how the consistent use of technology leads to automatic acceptance (Ballesteros et al., 2024). [40]. Numerous studies have demonstrated UTAUT2's adaptability in the educational domain (Meet et al., 2022; Tarhini et al., 2021). [41, 42]. The model also considers the ongoing importance of SI, which examines how peers, institutions, and society affect technology adoption and FC, and discusses the availability of tools and support needed for using technology. (Bayaga & Plessis 2023) [43]. Research conducted during the

COVID-19 pandemic further illustrated UTAUT2's adaptability and shed light on how teachers and students adjusted to distant learning resources. Its broad applicability in understanding user behaviour, motivation, and decision-making with regard to technology adoption is demonstrated by its usage in different industries, such as financial services, healthcare, and education (Gupta et al., 2023; Almisad & Alsalim, 2020) [44, [45]. UTAUT2 offers a comprehensive and adaptable strategy to help teachers understand why and how they use the DLR. Unlike its predecessor, it acknowledges that how technology is used is impacted by social dynamics, HBs, cost considerations, enjoyment, and ease of use. As a result, it is a powerful tool for lawmakers and educational establishments seeking to encourage effective and sustainable integration of digital learning. The proposed Conceptual framework of the study is shown in figure 1.

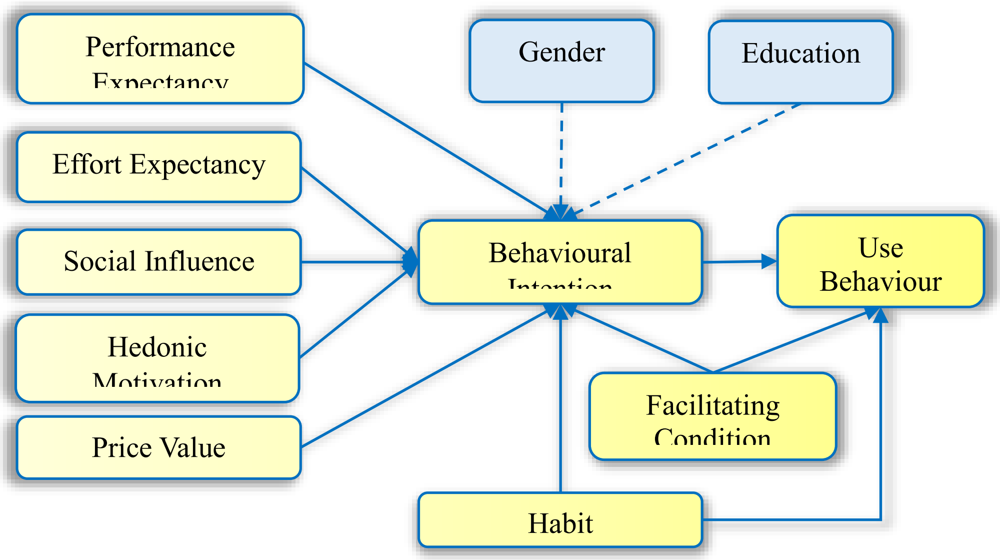


**Figure 1:** Conceptual Model of the Study

## 8. UNDERSTANDING HOW TEACHERS ACCEPT TECHNOLOGY IN EDUCATION: THE UTAUT2 MODEL:

Whether teachers actually use new technology in the classroom depends on a number of factors. PE, SI, EE, FC, PV, HM, and HB were the seven main components examined by the UTAUT2.

### 8.1 Performance Expectancy: Will Technology Help?

This has to do with how much educators believe that utilising technology will improve their teaching. Previous studies indicate that teachers are more inclined to embrace technology if teachers think that it would simplify their work. For example, an Indonesian study found that instructors who expected better teaching outcomes were more likely to adopt the Merdeka Mengajar platform (Aminah et al., 2024) [21]. According to studies on educational AI and MOOCs (online courses), teachers embrace these technologies because they think they would be helpful (Almenara et al., 2024; Tseng et al., 2019) [23, 27].

### 8.2 Effort Expectancy: Is It Easy to Use?

This component has to do with the user-friendliness and simplicity of the technology. Teachers might steer clear things if they are too difficult. According to a study on learning management systems (LMS), preservice instructors embrace these platforms mostly because they are easy to use (Raman and Don 2013) [24]. Another study also showed that more teachers are willing to employ an easy-to-use tool (Shah et al., 2020) [19].

### 8.3 Social Influence: What Do Others Think?

Individuals are frequently affected by their bosses, acquaintances, or coworkers. If teachers see others using technology, they are more likely to test it. According to research conducted in Malaysia and India, peer or expert support increased teachers' willingness to embrace new technologies (Ismail et al., 2022; Kundu et al., 2021) [25, 28].

### 8.4 Facilitating Condition: Are Resources Available?

Teachers require appropriate assistance such as infrastructure, management encouragement, and training, even if they wish to employ technology. According to certain studies, adoption is significantly influenced by available resources (Tseng et al., 2019) [27]. However, according to other research, having resources alone is insufficient, and motivation and HBs are important (Aminah et al., 2024) [21].

### 8.5 Hedonic Motivation: Is It Fun?

When people value technology, they are more likely to use it. According to previous research, when teachers find digital technologies engaging, they are more likely to apply them in the classroom (Almenara et al. 2024) [23]. This explains the increase in the popularity of interactive tools and gamified learning applications.

### 8.6 Price Value: Is this the worst cost?

Teachers and institutions could be reluctant to accept technology if it is too costly. According to previous research, PV is important, especially in settings with limited resources, when judgements about technology adoption are influenced by financial constraints (Aminah et al., 2024; Tseng et al., 2019). [21, 27].

### 8.7 Habit: Are teachers used to it?

The regular use of technology by teachers creates an HB that facilitates its adoption in the future. However, research has indicated that the HB is not always a reliable indicator of sustained usage. HB, for example, has no appreciable infleunce on teachers' sustained use of VR technology in the classroom, according to studies on the subject (Du & Liang, 2024) [22].

## 9. METHODOLOGY:

In Dakshina Kannada, India, factors influencing teachers' adoption of digital learning technologies were investigated using the UTAUT2 paradigm. PE, SI, EE, FC, PV, HM, and HB are the seven main constructs that make up UTAUT2 and aid in explaining technology acceptance behaviour. These concepts serve as the cornerstone for comprehending teachers' BIs and the real-world uses of digital learning materials. The study developed 10 main hypotheses to examine these aspects and the connections between these constructs and the use of digital learning tools by teachers. To evaluate the impact of demographic factors—gender, frequency of technology use, and field of study—on BI, three updated hypotheses were also presented. These hypotheses focused on group disparities in the adoption and usage patterns of digital resources. This study used a stratified random sampling technique and a quantitative research design. Teachers from the Dakshina Kannada district in Karnataka, India, which is administratively separated into nine taluks (sub-districts), were the target population. The sample consisted of 502 teachers, and the participants were selected in proportion to the entire population of each taluk. Because precise teacher population statistics for each taluk were unavailable, proportional allocation was based on the estimated total population of each taluk. Table 4 displays the relative sample size distributions for each taluk.

**Table 4:** Proportionate Sample Size Distribution Across Taluks

| Sl. No. | Taluk | Estimated Total Population | % Share to Total Population | Sample Size (Proportionate) |
|---|---|---|---|---|
| 1 | Mangaluru | 733,009 | 30.95% | **155** |
| 2 | Bantwala | 398,847 | 16.84% | **85** |
| 3 | Belthangadi | 302,157 | 12.76% | **64** |

| | | | | |
|---|---|---|---|---|
| 4 | Ullala | 241,173 | 10.18% | **51** |
| 5 | Puttur | 210,232 | 8.88% | **45** |
| 6 | Sulya | 144,665 | 6.11% | **31** |
| 7 | Kadaba | 135,961 | 5.74% | **29** |
| 8 | Moodabidri | 119,435 | 5.04% | **25** |
| 9 | Mulki | 82,969 | 3.50% | **18** |
| **Total** | | **2,368,448** | **100.00%** | **502** |

***Source:*** *(Directorate of Economics and Statistics, Planning Programme Monitoring and Statistics Department, 2022) [46]*

The following formula was used to proportionately determine the sample size for each taluk sample:

$$\textit{Sample Size for each Taluk} = \left(\textit{Total Population of Taluk}/\textit{Total Population}\right) \times 502$$

To guarantee widespread involvement, data were gathered using Google Forms and offline surveys. Over the course of 40 days, from November 2024 to January 2025, 866 responses were received. Missing data points were filled in using the median value to guarantee accuracy, and the responses were filtered and sorted based on the necessary taluk-wise distribution. Excess samples were eliminated to preserve the proportionate representation. A systematic questionnaire was created to gauge teachers' opinions regarding DLR adoption. Using a 5-point Likert scale, with "Strongly Agree" at the top and "Strongly Disagree" at the bottom, the items were changed to fit the educational setting and were derived from the existing UTAUT2 measures. This approach provided reliable insights into the factors influencing instructors' BIs and the use of online learning resources, while ensuring uniformity in data collection. The collected data were thoroughly analysed using a number of statistical techniques. Descriptive statistics, such as means, standard deviations, and normality tests, were employed to comprehend the sample characteristics. The validity and reliability of the measurement model were evaluated using Confirmatory Factor Analysis (CFA). Structural equation modelling (SEM) was used to examine the associations between UTAUT2 components. Additionally, group differences by gender, frequency of technology use, and field of study were examined using independent-sample t-tests and One-Way ANOVA.

## 10. RESULTS:

### 10.1 Demographic profile

Table 5 presents the respondents' demographic profiles, including gender, field of study, and frequency of technological use.

**Table 5:** Respondent’s demographic profile

| Variable Name | Options | Frequency | Percentage (%) |
|---|---|---|---|
| **Gender** | Male | 160 | 31.9 |
| | Female | 342 | 68.1 |
| | **Total** | **502** | **100.0** |
| **Field of Study** | Science | 265 | 52.8 |
| | Commerce & Business Studies | 149 | 29.7 |
| | Humanities/Arts | 88 | 17.5 |
| | **Total** | **502** | **100.0** |

| | | | |
|---|---|---|---|
| **Frequency of Technology Use** | Daily (Frequent user) | 81 | 16.1 |
| | A few times a week (Moderate user) | 161 | 32.1 |
| | A few times a month (Occasional user) | 211 | 42.0 |
| | Rarely or never (Rare user) | 49 | 9.8 |
| | **Total** | **502** | **100.0** |

***Source: Survey Data***

The sample include 160 male (31.9%) and 342 female (68.1 %) teachers. The majority of participants specialised in science (52.8%), followed by Commerce and Business Studies (29.7%), and humanities/arts (17.5%). Regarding the frequency of technology use, the largest group comprised occasional users (42.0%), followed by moderate (32.1%), frequent (16.1%), and rare users (9.8%).

### 10.2 Descriptive Statistics and Normality Analysis

Table 6 displays the study variables' descriptive statistics and normality analysis. Since mean values summarise overall response trends and reflect the data's central tendency, they must be reported. The standard deviation provides information on data variability by showing the distribution of the answers. For the parametric tests to be valid, normality must be evaluated. Kurtosis evaluates the peakedness of the data, whereas skewness gauges distribution symmetry. According to Byrne (2010), (quoted in Demir, 2022) [47] If the skewness and kurtosis of the data were within ±2 and ±7, respectively, they were considered normal. By disclosing these values, it is possible to ascertain whether the dataset satisfies the normalcy assumptions, thereby facilitating a sound statistical analysis.

**Table 6:** Descriptive Statistics and Normality Analysis

| | Mean | Std. Deviation | Variance | Skewness | Kurtosis |
|---|---|---|---|---|---|
| PE1 | 3.32 | 1.024 | 1.048 | -.098 | -.602 |
| PE2 | 3.32 | 1.099 | 1.208 | .009 | -.884 |
| PE3 | 3.34 | 1.033 | 1.067 | -.092 | -.614 |
| EE1 | 3.41 | 1.108 | 1.228 | -.183 | -.908 |
| EE2 | 3.34 | 1.117 | 1.248 | -.098 | -.993 |
| EE3 | 3.38 | 1.104 | 1.218 | -.151 | -.916 |
| HB1 | 3.52 | 1.032 | 1.064 | -.338 | -.430 |
| HB2 | 3.48 | 1.051 | 1.104 | -.258 | -.580 |
| HB3 | 3.50 | 1.088 | 1.185 | -.204 | -.739 |
| PV1 | 3.40 | 1.162 | 1.351 | -.318 | -.742 |
| PV2 | 3.37 | 1.166 | 1.358 | -.252 | -.822 |
| PV3 | 3.43 | 1.168 | 1.363 | -.242 | -.788 |
| HM1 | 3.47 | 1.086 | 1.180 | -.167 | -.749 |
| HM2 | 3.49 | 1.070 | 1.145 | -.264 | -.659 |
| HM3 | 3.48 | 1.085 | 1.176 | -.260 | -.735 |
| SI1 | 2.84 | 1.083 | 1.172 | .112 | -.790 |
| SI2 | 2.88 | 1.125 | 1.266 | .236 | -.711 |
| SI3 | 2.91 | 1.146 | 1.313 | .244 | -.824 |
| FC1 | 3.26 | 1.064 | 1.132 | .009 | -.808 |
| FC2 | 3.29 | 1.053 | 1.110 | -.031 | -.744 |
| FC3 | 3.36 | 1.051 | 1.105 | -.078 | -.670 |
| UB1 | 3.42 | 1.046 | 1.095 | -.218 | -.622 |
| UB2 | 3.39 | 1.068 | 1.140 | -.221 | -.776 |
| UB3 | 3.36 | 1.072 | 1.150 | -.118 | -.787 |
| BI1 | 3.50 | 1.020 | 1.041 | -.396 | -.392 |

| | | | | | |
|---|---|---|---|---|---|
| BI2 | 3.48 | 1.022 | 1.045 | -.300 | -.428 |
| BI3 | 3.50 | 1.010 | 1.021 | -.310 | -.348 |
| Valid N (listwise): 502 | | | | | |

***Source: Statistical Analysis of Survey data***

The mean values fall between 2.84 and 3.52, indicating a generally moderate level of agreement across the constructs. PE (3.32–3.34) suggests that teachers perceive DLR as somewhat useful, while EE (3.34–3.41) indicates that teachers perceive the technology moderately easy to use. HB (3.48–3.52) and BI (BI) (3.48–3.50) showed the highest mean values, suggesting that prior experience strongly influences continued use, and that teachers intend to continue using digital resources. In contrast, SI (2.84–2.91) has the lowest mean, implying that external encouragement plays a minor role in adoption. FC (3.26–3.36), PV (3.37–3.43), and HM (3.47–3.49) indicate that teachers acknowledge the importance of support structures, cost-effectiveness, and enjoyment but do not strongly emphasise these factors. Regarding normality, all skewness values were within the range of ±2, indicating approximate symmetry in the data distribution. The values ranged from -0.396 (BI1) to 0.244 (SI3), suggesting slight skewness in some variables, but none showed extreme asymmetry. Similarly, all kurtosis values fell within the acceptable threshold of ±7, confirming the absence of extreme peakedness or flatness. The values range from -0.348 (BI3) to -0.993 (EE2), showing a slightly platykurtic distribution (flatter than normal), which does not violate the normality assumptions. These findings confirm that the dataset meets the normality requirements, supporting the validity of parametric statistical analyses.

### 10.3 Gender Differences in BI

This study examined whether male and female teachers use digital learning resources for different behavioural reasons. Because gender is categorical (male/female) and BI is scored on a Likert scale, this test is appropriate. Table 7 below shows the summary of the t-test for Gender differences in BI.

**Table 7:** Independent Samples t-test Results for Gender Differences in BI

| Variable | Gender | N | Mean | Std. Dev. | t | df | Mean Diff. | Std. Error Diff. | Sig. (2-tailed) |
|---|---|---|---|---|---|---|---|---|---|
| **BI1** | Male | 160 | 3.60 | 0.966 | 1.444 | 500 | 0.141 | 0.098 | **.149** |
| | Female | 342 | 3.46 | 1.043 | | | | | |
| **BI2** | Male | 160 | 3.58 | 0.994 | 1.459 | 500 | 0.143 | 0.098 | **.145** |
| | Female | 342 | 3.44 | 1.033 | | | | | |
| **BI3** | Male | 160 | 3.57 | 0.982 | 1.103 | 500 | 0.107 | 0.097 | **.270** |
| | Female | 342 | 3.46 | 1.023 | | | | | |

***Source: Statistical Analysis of Survey data***

Gender differences in BI were investigated using an independent sample t-test. There were no notable differences between male and female participants for BI1, $t(500) = 1.444$, $p = .149$; BI2, $t(500) = 1.459$, $p = .145$; and BI3, $t(500) = 1.103$, $p = .270$, according to the results. These results imply that BI is not significantly affected by Gender.

### 10.4 Frequency of Technology Use and BI

Study determined whether teachers' intentions to behave are significantly impacted by how they use technology. Because usage frequency is a categorical variable with many levels, ANOVA was used to look for differences. Table 8 displays the results of the ANOVA for BI and frequency of technology use.

**Table 8:** One-Way ANOVA for Frequency of Technology Use and BI

| | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| **BI1** | Between Groups | 318.205 | 3 | 106.068 | 259.840 | **.000** |
| | Within Groups | 203.287 | 498 | .408 | | |
| | Total | 521.492 | 501 | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| **BI2** | Between Groups | 307.909 | 3 | 102.636 | 237.224 | **.000** |
| | Within Groups | 215.463 | 498 | .433 | | |
| | Total | 523.373 | 501 | | | |
| **BI3** | Between Groups | 329.294 | 3 | 109.765 | 300.017 | **.000** |
| | Within Groups | 182.198 | 498 | .366 | | |
| | **Total** | **511.492** | **501** | | | |

***Source: Statistical Analysis of Survey data***

One-way ANOVA was used to examine how the frequency of technology use affected BI. The results indicated a significant effect for BI1, $F(3, 498) = 259.84$, $p < .005$; BI2, $F(3, 498) = 237.22$, $p < .005$; and BI3, $F(3, 498) = 300.02$, $p < .005$. These findings suggest that BI varies significantly, depending on the frequency of technology use.

### 10.5 Field of Study and BI

Teachers from different fields of study were examined for BI towards digital learning materials using one-way ANOVA. ANOVA facilitates the comparison of mean scores, because the field of study is a categorical variable. The ANOVA results for BI and field of study are shown in Table 9.

**Table 9:** One-Way ANOVA for Field of Study and BI

| | | **Sum of Squares** | **df** | **Mean Square** | **F** | **Sig.** |
|---|---|---|---|---|---|---|
| **BI1** | Between Groups | 209.006 | 2 | 104.503 | 166.878 | **.000** |
| | Within Groups | 312.486 | 499 | .626 | | |
| | Total | 521.492 | 501 | | | |
| **BI2** | Between Groups | 185.452 | 2 | 92.726 | 136.926 | **.000** |
| | Within Groups | 337.921 | 499 | .677 | | |
| | Total | 523.373 | 501 | | | |
| **BI3** | Between Groups | 212.964 | 2 | 106.482 | 177.989 | **.000** |
| | Within Groups | 298.528 | 499 | .598 | | |
| | **Total** | **511.492** | **501** | | | |

***Source: Statistical Analysis of Survey data***

The results indicated a significant effect for BI1, $F(2, 499) = 166.88$, $p < .005$; BI2, $F(2, 499) = 136.93$, $p < .005$; and BI3, $F(2, 499) = 177.99$, $p < .005$. These findings suggest that BI differs significantly depending on the field of study.

### 10.6 Measurement Model

Confirmatory Factor Analysis CFA in SPSS AMOS was used to evaluate the relationships between latent and observable variables using the Measurement Model. By examining the reliability and validity of constructs, CFA is an essential stage in structural equation modelling (SEM) that guarantees that the data match the suggested theoretical framework (Pasupuleti, 2024; Huang et al., 2023) [48, 49]. Whether the measured variables accurately reflect the underlying factors influencing instructors' BI to use learning resources was tested here. By using convergent and discriminant validity tests to confirm the measurement structure's resilience, the CFA enhanced the study's overall integrity (Nguyen & Habók, 2022; Shuriye & Muse, 2023) [50, 51]. This study strengthens the theoretical underpinnings of technology adoption in education by incorporating CFA into the Measurement Model, which guarantees that the research findings are founded on valid and trustworthy notions (Dewi et al., 2023) [52]. Figure 2 below display measurement model.

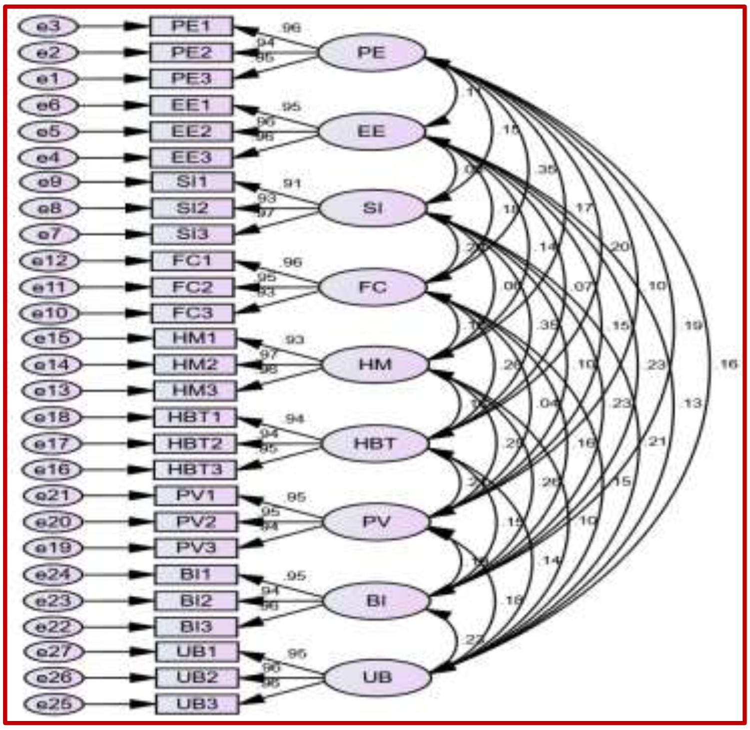


**Figure 2:** Measurement Model

### *10.6.1 Model Fit indices of Measurement Model*

Model fit indices are crucial criteria in CFA for evaluating the effectiveness of a measurement model. The Goodness of Fit Index (GFI), Tucker-Lewis Index (TLI), Normed Fit Index (NFI), and Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA) are essential for assessing model fit, claim Sathyanarayana and Mohanasundaram (2024) [53]. To determine whether their models meet the recognised statistical norms, researchers employ acceptable and goodness-value thresholds. Table 10 presents he extracted values of the model fit indices and the corresponding acceptable and good fit thresholds.

**Table 10:** Model Fit indices of Measurement Model

| Fit Index | Obtained | Threshold for Acceptable Fit | Threshold for Good Fit | Reference |
|---|---|---|---|---|
| Goodness of Fit Index (GFI) | 0.912 | ≥ 0.90 | ≥ 0.95 | (Sathyanarayana & Mohanasundaram, 2024) (Hair et al., 2019) [53, 54] |
| Chi-Square/Degrees of Freedom (CMIN/DF) | 2.284 | ≤ 3.0 | ≤ 2.0 | |
| Normed Fit Index (NFI) | 0.962 | ≥ 0.90 | ≥ 0.95 | |
| Relative Fit Index (RFI) | 0.954 | ≥ 0.90 | ≥ 0.95 | |
| Incremental Fit Index (IFI) | 0.978 | ≥ 0.90 | ≥ 0.95 | |
| Tucker-Lewis Index (TLI) | 0.974 | ≥ 0.90 | ≥ 0.95 | |
| Comparative Fit Index (CFI) | 0.978 | ≥ 0.90 | ≥ 0.95 | |
| Root Mean Square Error of Approximation (RMSEA) | 0.051 | ≤ 0.08 | ≤ 0.06 | |

***Source: Statistical Analysis of Survey data***

A well-fitting measurement model was shown by all model fit indices that met permissible levels. The GFI (0.912), NFI (0.962), RFI (0.954), IFI (0.978), TLI (0.974), and CFI (0.978) exceeded 0.90, confirming a good fit. CMIN/DF (2.284) was within the acceptable range (≤ 3.0) and RMSEA (0.051) indicated a strong fit (≤ 0.06).

### *10.6.2 Reliability and Validity of measurement model*

The validity and reliability of the measurement model allowed for a precise evaluation of the associated latent constructs using observable data. Reliability was assessed using Cronbach's alpha (α) and Composite Reliability (CR); values above 0.70 suggested strong internal consistency (Hair et al., 2019) [54]. Convergent validity was tested using the Average Variance Extracted (AVE) and standardised regression weights (≥ 0.70); constructs that effectively account for the variance in their indicators are said to have AVE values greater than 0.50 (Henseler et al., 2015; Fornell & Larcker, 1981) [56,57]. Table 11 displays the results' validity and dependability.

**Table 11:** Validity and reliability of measurement model

| Latent Construct | Observed Variable | Standardized Regression Weight (Estimate) | Cronbach's Alpha (α) | Composite Reliability (CR) | Average Variance Extracted (AVE) |
|---|---|---|---|---|---|
| PE | PE3 | 0.954 | 0.944 | 0.965 | 0.902 |
| | PE2 | 0.937 | | | |
| | PE1 | 0.959 | | | |
| EE | EE3 | 0.965 | 0.941 | 0.971 | 0.918 |
| | EE2 | 0.956 | | | |
| | EE1 | 0.954 | | | |
| SI | SI3 | 0.973 | 0.946 | 0.957 | 0.880 |
| | SI2 | 0.931 | | | |
| | SI1 | 0.909 | | | |
| FC | FC3 | 0.930 | 0.945 | 0.965 | 0.901 |
| | FC2 | 0.954 | | | |
| | FC1 | 0.963 | | | |
| HM | HM3 | 0.960 | 0.948 | 0.968 | 0.910 |
| | HM2 | 0.968 | | | |
| | HM1 | 0.933 | | | |
| HB | HB3 | 0.949 | 0.931 | 0.962 | 0.893 |
| | HB2 | 0.943 | | | |
| | HB1 | 0.943 | | | |
| PV | PV3 | 0.938 | 0.933 | 0.963 | 0.897 |
| | PV2 | 0.949 | | | |
| | PV1 | 0.954 | | | |
| BI | BI3 | 0.956 | 0.934 | 0.964 | 0.899 |
| | BI2 | 0.939 | | | |
| | BI1 | 0.950 | | | |
| UB (UB) | UB3 | 0.957 | 0.938 | 0.968 | 0.910 |
| | UB2 | 0.955 | | | |
| | UB1 | 0.950 | | | |

***Source: Statistical Analysis of Survey data***

Cronbach's alpha (α) values (0.931–0.948) over 0.70 indicated internal consistency. Composite Reliability (CR) values greater than 0.90. Average Variance Extracted (AVE) values (0.880–0.918) of greater than 0.50. Additionally, highly standardised regression weights (≥0.90) were used to validate the components. These outcomes demonstrate that the model is appropriate for structural analysis.

### *10.6.3 Discriminant Validity Analysis using Fornell-Larcker criterion*

Discriminant validity guarantees the distinction between the constructs in the model. By comparing the square root of AVE with inter-construct correlations, which ought to be greater than the correlations between components, the Fornell-Larcker criterion (Fornell & Larcker, 1981) [57] evaluates this. Furthermore, to verify the construct validity, the Composite Reliability (CR) must be greater than 0.70 and the Maximum Shared Variance (MSV) must be less than the AVE. The CR, AVE, MSV, and inter-construct correlations for each construct are presented in Table 12.

**Table 12:** Discriminant Validity Analysis

| | CR | AVE | MSV | MaxR (H) | PE | EE | SI | FC | HM | HB | PV | BI | UB |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **PE** | 0.965 | 0.902 | 0.125 | 0.966 | 0.950 | | | | | | | | |
| **EE** | 0.971 | 0.918 | 0.052 | 0.972 | 0.112 | 0.958 | | | | | | | |
| **SI** | 0.957 | 0.880 | 0.123 | 0.967 | 0.152 | 0.077 | 0.938 | | | | | | |
| **FC** | 0.965 | 0.901 | 0.125 | 0.967 | 0.354 | 0.178 | 0.204 | 0.949 | | | | | |
| **HM** | 0.968 | 0.910 | 0.070 | 0.971 | 0.168 | 0.135 | 0.056 | 0.176 | 0.954 | | | | |
| HB | 0.962 | 0.893 | 0.123 | 0.962 | 0.200 | 0.067 | 0.351 | 0.264 | 0.158 | 0.945 | | | |
| PV | 0.963 | 0.897 | 0.063 | 0.964 | 0.099 | 0.148 | 0.098 | 0.039 | 0.251 | 0.214 | 0.947 | | |
| BI | 0.964 | 0.899 | 0.070 | 0.965 | 0.191 | 0.228 | 0.231 | 0.158 | 0.264 | 0.149 | 0.191 | 0.948 | |
| UB | 0.968 | 0.910 | 0.054 | 0.968 | 0.163 | 0.127 | 0.211 | 0.154 | 0.100 | 0.137 | 0.179 | 0.233 | 0.954 |

***Source: Statistical Analysis of Survey data***

PE (0.950), EE (0.958), SI (0.938), FC (0.949), HM (0.954), HB (0.945), PV (0.947), Behavioural Intention (0.948), and Use Behaviour (0.954) had diagonal correlations that were higher than their respective off-diagonal levels. This supports the validity of the measurement model by demonstrating how unique each construct is from the others.

### *10.6.3 HTMT Analysis for Discriminant Validity*

The heterotrait–monotrait ratio (HTMT) [56] is an additional technique for evaluating discriminant validity (Henseler et al., 2015). Rigorous discriminant validity is indicated by values below 0.85 (Hu & Bentler, 1999) [58]. This approach strengthens the measurement model's resilience by preventing substantial overlap between constructs. Table 13 presents the HTMT values for each construct.

**Table 13:** HTMT Analysis for Discriminant Validity

| | PE | EE | SI | FC | HM | HB | PV | BI |
|---|---|---|---|---|---|---|---|---|
| **EE** | 0.108 | | | | | | | |
| **SI** | 0.150 | 0.076 | | | | | | |
| **FC** | 0.356 | 0.176 | 0.203 | | | | | |
| **HM** | 0.161 | 0.137 | 0.063 | 0.166 | | | | |
| **HB** | 0.204 | 0.068 | 0.347 | 0.269 | 0.156 | | | |
| **PV** | 0.099 | 0.147 | 0.102 | 0.043 | 0.256 | 0.215 | | |
| **BI** | 0.190 | 0.225 | 0.232 | 0.158 | 0.262 | 0.149 | 0.189 | |
| **UB** | 0.163 | 0.130 | 0.204 | 0.155 | 0.100 | 0.137 | 0.180 | 0.233 |

***Source: Statistical Analysis of Survey data***

Discriminant validity was validated by HTMT analysis because every value was below the more stringent cutoff of 0.85. The maximum HTMT value recorded between PE and FC was 0.356, which was within the permissible range. This suggests that the conceptions are sufficiently different to minimise multicollinearity issues and support the validity of the measurement model.

## 10.7 Path Analysis Model in Structural Equation Modeling (SEM)

Path analysis was employed because it enables the evaluation of several direct and indirect links between latent constructs simultaneously, offering a thorough comprehension of the ways in which variables affect BI (BI) and use behaviour (UB). Standardised regression weights, measurement errors, and observable variables are all included in the analysis to guarantee validity and reliability. The path analysis model depicted in Figure 3 was utilised to examine the study's primary hypotheses.

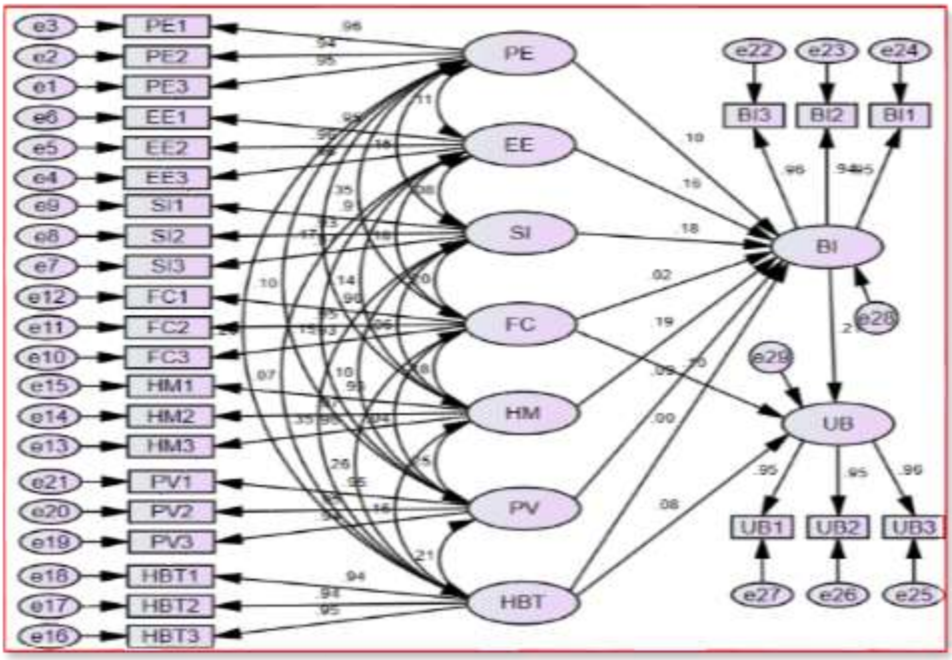


**Figure 3:** Path Analysis Model

### *10.7.1 Model Fit Indices of Path Model*

Table 14 below shows the obtained values of key model fit indices along with their acceptable and good fit thresholds of Path Model

**Table 14:** Model Fit Indices of Path Model

| Fit Index | Obtained Value | Threshold for Acceptable Fit | Threshold for Good Fit | Reference |
|---|---|---|---|---|
| **GFI** | 0.910 | ≥ 0.90 | ≥ 0.95 | (Sathyanarayana & Mohanasundaram, 2024) (Dr. Raghavendra & Shruthi N., 2025) (Hair et al., 2019) [53, 54, 55] |
| **CMIN/DF** | 2.311 | ≤ 3.0 | ≤ 2.0 | |
| **NFI** | 0.961 | ≥ 0.90 | ≥ 0.95 | |
| **RFI** | 0.954 | ≥ 0.90 | ≥ 0.95 | |
| **IFI** | 0.978 | ≥ 0.90 | ≥ 0.95 | |
| **TLI** | 0.973 | ≥ 0.90 | ≥ 0.95 | |
| **CFI** | 0.978 | ≥ 0.90 | ≥ 0.95 | |
| **RMSEA** | 0.051 | ≤ 0.08 | ≤ 0.06 | |

***Source: Statistical Analysis of Survey data***

## 10.8 Hypothesis Testing

Hypothesis testing was performed using SEM to investigate the relationships between the primary constructs in the suggested model. The analysis evaluated path coefficients (estimate β), Standard Error (S.E.), Critical Ratio (C.R.), and p-values to determine the statistical significance of each suggested relationship. Strong support for a particular hypothesis is shown by a p-value ≤ 0.05, but at the 95% confidence level, statistical significance is implied by a C.R. larger than 1.96. The results presented in Table 15 provide insights into the direct effects of study variables. The theoretical framework was validated, and strategies for increasing the uptake of digital learning were influenced by the classification of each hypothesis as either supported or not supported. To determine whether demographic and contextual factors affected BI, a group difference analysis was also conducted as summarised in Table 16.

**Table 15:** Primary Hypothesis Testing Results

| Hypothesis | Path | Estimate (β) | S.E. | C.R. | p-value | Decision |
|---|---|---|---|---|---|---|
| **H1** | PE → BI | 0.096 | 0.045 | 2.110 | 0.035 | **Supported** |
| **H2** | EE → BI | 0.146 | 0.040 | 3.671 | *** | **Supported** |
| **H3** | SI → BI | 0.157 | 0.040 | 3.926 | *** | **Supported** |
| **H4** | HM → BI | 0.175 | 0.042 | 4.191 | *** | **Supported** |
| **H5** | PV → BI | 0.082 | 0.040 | 2.048 | 0.041 | **Supported** |
| **H6** | HB → BI | 0.000 | 0.045 | -0.004 | 0.996 | **Not Supported** |
| **H7** | HB → UB | 0.082 | 0.046 | 1.766 | 0.077 | **Not Supported** |
| **H8** | FC → UB | 0.106 | 0.049 | 2.161 | 0.031 | **Supported** |
| **H9** | FC → BI | 0.021 | 0.047 | 0.445 | 0.657 | **Not Supported** |
| **H10** | BI → UB | 0.220 | 0.048 | 4.548 | *** | **Supported** |

***Source: Compiled by Author's***

**Table 16:** Summary of Group Difference Hypothesis Testing

| Hypothesis | Test Used | Significant? (p < .05) | Decision |
|---|---|---|---|
| **H10a** | Independent t-test | No (p > .05 for all BI items) | **Not Supported** |
| **H10b** | One-Way ANOVA | Yes (p < .005 for all BI items) | **Supported** |
| **H10c** | One-Way ANOVA | Yes (p < .005 for all BI items) | **Supported** |

***Source: Compiled by Author's***

PE ($\beta = 0.096$, $p = 0.035$), EE ($\beta = 0.146$, $p < 0.001$), SI ($\beta = 0.157$, $p < 0.001$), HM ($\beta = 0.175$, $p < 0.001$), and PV ($\beta = 0.082$, $p = 0.041$) all significantly improved BI, according to the results of the hypothesis test in Table 15. Moreover, Use Behaviour (UB) was significantly impacted by FC ($\beta = 0.106$, $p = 0.031$) and BI ($\beta = 0.220$, $p < 0.001$). Nevertheless, HB had no discernible effect on either use behaviour ($\beta = 0.082$, $p = 0.077$) or BI ($\beta = 0.000$, $p = 0.996$). Likewise, FC had no appreciable impact on the (BI) ($\beta = 0.021$, $p = 0.657$). There was no significant difference ($p > 0.05$) in gender-based behavioural intention (BI) according to the group difference analysis. However, significant differences found in the frequency of technology use ($p < 0.05$) and the teacher's field of study ($p < 0.05$).

## 11. DISCUSSION:

According to this study, several important factors had a substantial impact on instructors' BI and use behaviour (UB) with reference to DLR. The findings presented in Table 15 confirm the validity of the theoretical model by offering substantial empirical evidence for the majority of assumptions.

### 11.1 Performance Expectancy and Behavioural Intention

As per this study, PE has a substantial influence on BI ($\beta = 0.096$, C.R. = 2.110, $p = 0.035$). According to Shah et al. (2021) [19] and Aminah et al. (2024) [21], teachers are more likely to adopt technology when they see their obvious educational advantages. Therefore, study's results is consistent with their findings. Given the importance of physical education, it is possible to increase the adoption of digital tools by showcasing how well they improve educational outcomes.

### 11.2 Effort Expectancy and Behavioural Intention

EE had a substantial impact on BI ($\beta = 0.146$; CR = 3.671, $p < 0.001$), suggesting that teachers preferred user-friendly digital learning resources. This in cope with the results of Ismail et al. (2022) [25] and

Rodríguez-Gil (2024) [20], who found that pre-service and in-service teachers' use of technology is greatly influenced by simplicity of use. These results emphasise the importance of creating DLRs that are easy to use to promote their broad adoption.

### 11.3 Social Influence and Behavioural Intention

The results of Tseng et al. (2022) [27] and Shah et al. (2021) [19] were supported by SI's significant prediction of BI ($\beta = 0.157$, C.R. = 3.926, $p < 0.001$). Teachers who feel supported by their peers, administrators, and students are more likely to implement DLR, highlighting the importance of collaborative learning and institutional support.

### 11.4 Hedonic Motivation and Behavioural Intention

HM had a substantial impact on BI ($\beta = 0.175$; CR). = 4.191, $p < 0.001$), indicating that the adoption was boosted by the enjoyment of digital tools. According to Rodríguez-Gil (2024) [20] and Cabero-Almenara et al. (2024) [23], adoption is positively affected by interactive and engaging technologies. These findings suggest that adding immersive and gamified components to DLR can increase teachers' interest in using these tools.

### 11.5 Price Value and Behavioural Intention

PV was found to be an important factor influencing BI ($\beta = 0.082$, CR). = 2.048, $p = 0.041$). This result cope with that of Aminah et al. (2024) [21], who reported that cost-benefit considerations play a role in educational app adoption. However, Rodríguez-Gil (2024) [20] found that PV had a minimal impact on iVR adoption, indicating that financial concerns may vary based on the type of technology and institutional funding.

### 11.6 Habit, Behavioural Intention and Use Behaviour

HB did not significantly influence the BI ($\beta = 0.000$; CR). = -0.004, $p = 0.996$) or UB ($\beta = 0.082$, C.R. = 1.766, $p = 0.077$). These results contrast with those of Avci (2022) [1], who found that HB strongly predicted digital resource adoption. Similarly, Du and Liang (2024) [22] and Raman and Don (2013) [24] reported that HB does not always encourage sustained technological use. This suggests that teachers may require continuous institutional support rather than relying on their past technological experiences.

### 11.7 Facilitating Condition, Behavioural Intention and Use Behaviour

FC significantly predicted UB ($\beta = 0.106$; CR). = 2.161, $p = 0.031$) but not BI ($\beta = 0.021$, C.R. = 0.445, $p = 0.657$). This cope with the findings of Chroustová et al. (2022) [26] and Aminah et al. (2024) [21], who found that, while FC influences actual use, it does not necessarily drive initial adoption. These findings reinforce the need for infrastructure, and institutional initiatives in order to ensure sustained technological use.

### 11.8 Behavioural Intention and Use Behaviour

BI significantly predicted UB ($\beta = 0.220$, C.R. = 4.548, $p < 0.001$), reinforcing the theoretical framework. This aligns with Avci (2022) [1] and Tseng et al. (2022) [27], who reported that strong BI leads to actual technology adoption. Strengthening BI through targeted interventions can effectively enhance teachers' use of learning resources.

### 11.9 Group Differences in BI

#### *11.9.1 Gender (H10a)*

The Gender-based BI did not differ significantly ($p > 0.05$) for all BI items. This result is in cope with previous studies that indicate that teachers' adoption of technology is not significantly influenced by gender (Kundu et al. 2021) [28].

#### *11.9.2 Frequency of Technology Use (H10b)*

A significant difference in BI was observed based on the Frequency of Technology Use ($p < 0.001$ for all BI items). Teachers who frequently used technology reported higher BI, reinforcing the role of prior exposure in developing adoption intentions. This supports the findings of Avci (2022) [1], who reported that previous technology use significantly affected teachers' BIs.

#### *11.9.3 Field of Study (H10c)*

A significant difference in BI was found based on the Field of Study (P < 0.001 for all BI items). Teachers from fields that were more aligned with technology integration, such as STEM and Educational Technology, reported higher BI than those from non-STEM backgrounds. This aligns with Chroustová et al. (2022) [26], who found that subject-specific factors influence technology adoption.

### 11.10 Theoretical Implications

This study had two theoretical implications. First, the results affirm that the core UTAUT2 constructs remain robust predictors of teachers' adoption of DLR, underscoring the framework's general applicability in educational contexts. Second, although explicit moderators were not used, the analysis through grouping variables (such as the frequency of technology use and field of study) revealed distinct differences in adoption intentions across subgroups. These grouping differences provide nuanced insights into how contextual factors shape technology acceptance, thereby enhancing our theoretical understanding of the model's generalisability across diverse educational settings.

### 11.11 Practical Implications

***11.11.1 Enhanced Training and Support:*** Institutions should invest in targeted training programs that emphasise the ease of use of digital learning tools. Tailored support can address the distinct needs of different teacher groups, particularly those with less prior exposure to technology.

***11.11.2 User-Friendly Design:*** Technology providers must focus on developing intuitive, user-friendly interfaces that minimise the learning curve, thereby boosting teachers' confidence and encouraging sustained usage.

***11.11.3 Leveraging SI:*** Given the significant impact of SI on BI, fostering a culture of peer support and a collaborative learning environment can promote wider adoption. Encouraging experienced teachers to mentor their peers may amplify this effect.

***11.11.4 Infrastructure Investment:*** To ensure that FC is met, institutions must provide reliable technical infrastructure and readily available support services. This includes ensuring that the necessary hardware, software, and connectivity support the use of learning resources.

***11.11.5 Tailored Interventions for Digital Learning Adoption:*** This study indicates that teachers' adoption of DLR varies significantly based on how frequently they use technology and their academic disciplines. This suggests that institutions should develop tailored training and support programmes. For example, teachers with less frequent technology use may require more intensive hands-on training and ongoing technical support to build their confidence and competence. Strategies should be designed to address the unique challenges and needs of different academic disciplines. By implementing discipline-specific approaches, institutions can optimise adoption strategies across various educational contexts.

## 12. CONCLUSION:

The results, which are based on a UTAUT2 framework, demonstrate that teachers' behavioural intentions (BIs) and actual use of digital learning tools are significantly influenced by key constructs such as Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), Price Value (PV), and habitat (HB). The findings also show that adoption rates differ depending on the academic discipline and the frequency of technology use, underscoring the need for specialised training and support initiatives. These results empirically demonstrate that these variables accurately predict technology adoption among instructors, as opposed to lecturers or professors, and provide theoretical justification for the UTAUT2 model's suitability for use in educational settings. Practically speaking, educational institutions must concentrate on creating differentiated interventions that cater to the distinctive requirements of instructors, especially those who use technology less frequently and teach subjects with particular difficulties. Digital learning resources can be successfully integrated with the help of focused support and strong technical infrastructure.

Although the study provides insightful information, it is constrained by its exclusive emphasis on instructors from various universities, leaving out other academic positions, such as professors and lecturers. Longitudinal designs and a wider range of stakeholders should be considered in future studies to document changes over time and improve the adoption strategies for digital learning education.

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