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Factors Influencing The Adoption Of Subscription-Based E-Learning Platforms By Students In Dakshina Kannada

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Abstract

This study examines factors influencing students' adoption of subscription-based e-learning platforms in Dakshina Kannada, focusing on perceived ease of use (PEOU), perceived usefulness (PU), and attitude toward e-learning (ATE). Using the Technology Acceptance Model (TAM), the study explores how PEOU and PU affect students' behavioural intention to use (BIU) these platforms, with ATE mediating this relationship. A sample of 200 students was surveyed using structured questionnaires, and data were analyzed with Structural Equation Modeling (SEM). The results show that PEOU significantly impacts both ATE and BIU, while PU directly influences BIU. Furthermore, a positive attitude toward e-learning enhances students' intention to adopt these platforms. These findings underscore the importance of user-friendly design and clear demonstration of educational benefits in fostering e-learning adoption. The implications are significant for e-learning developers and educational institutions. Emphasizing ease of use and highlighting the practical benefits of e-learning platforms can drive higher adoption rates and enhance student engagement. This research provides valuable insights into technology acceptance in education and offers actionable recommendations for improving e-learning platform effectiveness.

Keywords: Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Behavioral Intention to Use (BIU), Attitude Toward E-Learning (ATE), Subscription-Based E-Learning Platforms

1. INTRODUCTION:

The adoption of e-learning platforms among students is a critical area of study, especially in regions like Dakshina Kannada. Understanding the factors that influence students' acceptance of subscription-based e-learning platforms is essential for educational institutions and policymakers. One of the prominent models used to analyze technology acceptance is the Technology Acceptance Model (TAM). The TAM was developed to explain and predict user acceptance of information technology (Venkatesh et al., 2003). It focuses on perceived ease of use and perceived usefulness as key determinants of user acceptance (Venkatesh et al., 2003). Previous research has shown that factors such as perceived ease of use, perceived usefulness, attitude toward e-learning, flexibility, and content quality positively impact students' behavioural intention to adopt e-learning platforms (Salybekova, 2023). Additionally, studies have highlighted the importance of social influence, self-efficacy, and previous experience in shaping students' acceptance of e-learning platforms (Pratama et al., 2022). Moreover, the TAM has been extended to examine users' continuous intention toward the utilization of e-learning platforms, emphasizing the significance of understanding factors that influence students' intention to continue using e-learning platforms to enhance their learning experience (Obeid, 2024). Furthermore, the model has been applied in various contexts, such as exploring the adoption of mobile learning systems among university students Pramana (2018) and identifying factors affecting medical students' acceptance of e-learning (Alsharafi, 2023). In light of the COVID-19 pandemic, which has accelerated the adoption of e-learning platforms, it is crucial to investigate how factors like social influences impact individuals' intention to adopt e-learning technologies (Acharjya & Das, 2021). Studies have also emphasized the role of push-pull-mooring effects, perceived security risk, learning convenience, service quality, and habit in influencing users' switching intentions to online learning platforms (Lin et al., 2021; Lisana, 2022). Additionally, perceived enjoyment and perceived usefulness have been identified as significant factors in the adoption of mobile learning (Pramana, 2018). Therefore, this study aims to explore the factors influencing the adoption of subscription-based e-learning platforms by students in Dakshina Kannada, drawing on the TAM and insights from previous research to provide valuable recommendations for educational stakeholders.

2. RESEARCH OBJECTIVES:

- To examine the impact of perceived ease of use on students' behavioural intention to adopt subscription-based e-learning platforms in Dakshina Kannada.
- To analyze the influence of perceived usefulness on students' behavioural intention to adopt subscription-based e-learning platforms in Dakshina Kannada.
- To investigate the role of attitude toward e-learning in determining students' behavioural intention to adopt subscription-based e-learning platforms.

3. RESEARCH HYPOTHESES:

H1: Perceived ease of use has a positive impact on students' behavioural intention to adopt subscription-based e-learning platforms in Dakshina Kannada.

H2: Perceived usefulness positively influences students' behavioural intention to adopt subscription-based e-learning platforms in Dakshina Kannada.

H3: Perceived usefulness positively influences students' Attitudes toward e-learning in Dakshina Kannada.

H4: Attitude toward e-learning has a positive effect on students' behavioural intention to adopt subscription-based e-learning platforms.

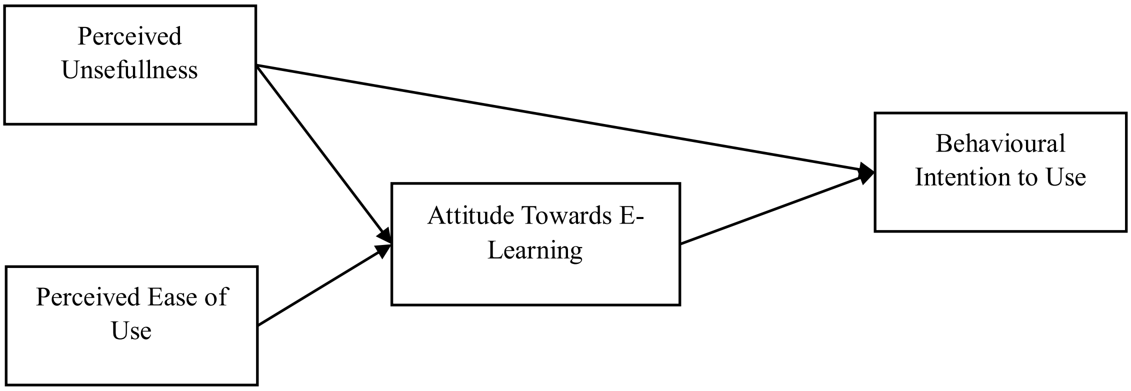


Figure 1: Proposed Conceptual Framework

4. LITERATURE REVIEW

The adoption of e-learning platforms has been the subject of extensive research, especially in the context of higher education. Various studies have employed the Technology Acceptance Model (TAM) to understand the factors influencing the adoption of these platforms.

Obeid (2024) focused on the continuous intention to use e-learning platforms among university students in Egypt. The study emphasized the significance of perceived usefulness and user satisfaction in determining students' continuous usage intentions. It also suggested that enhancing content quality and user interface could improve students' overall experience and intention to continue using the platforms.

Alsharafi (2023) examined the acceptance of e-learning platforms among medical students in Saudi Arabia. The study utilized an extended TAM and found that perceived usefulness, perceived ease of use, and attitude toward e-learning were significant predictors of students' intention to adopt e-learning platforms. The study also highlighted the importance of technical support and infrastructure in enhancing students' acceptance.

Salybekova (2023) investigated the factors influencing the adoption of e-learning platforms in Kazakhstan. The study found that perceived ease of use, perceived usefulness, and attitude toward e-learning were significant predictors of students' behavioural intentions. Additionally, the study highlighted the role of social influence and perceived security in shaping students' acceptance of e-learning.

Sharma et al. (2023) conducted a study on the adoption of subscription-based e-learning platforms among management students in Delhi. The study found that perceived usefulness and social influence were the most significant predictors of students' intention to adopt these platforms. The study also emphasized the role of content quality and perceived security in shaping students' attitudes toward e-learning.

Lisana (2022) examined the impact of perceived enjoyment and perceived usefulness on the adoption of mobile learning platforms in Malaysia. The study found that both factors significantly influenced students' behavioural intentions, with perceived enjoyment having a stronger impact on students' acceptance.

Pratama et al. (2022) explored the factors influencing the adoption of e-learning platforms in Indonesia using the TAM. The study identified perceived ease of use, perceived usefulness, and social influence as key determinants of students' behavioural intentions. Additionally, self-efficacy and previous experience with e-learning were found to significantly influence students' acceptance.

Rao and Kumar (2022) examined the impact of perceived usefulness and attitude toward e-learning on the behavioural intention of engineering students in South India. The results indicated that both factors significantly influenced students' intentions, with perceived usefulness having a stronger impact.

Acharjya and Das (2021) analyzed the impact of social influence on the adoption of e-learning platforms during the COVID-19 pandemic in Bangladesh. The study found that social influence, along with perceived ease of use and perceived usefulness, significantly impacted students' behavioural intentions. The study also highlighted the importance of institutional support in enhancing students' acceptance of e-learning.

Kumar and Singh (2021) explored the factors affecting the adoption of mobile learning among university students in India. The study identified perceived ease of use, perceived usefulness, and self-efficacy as critical factors. It also highlighted the importance of content quality and learning flexibility in enhancing students' acceptance of mobile learning.

Lin et al. (2021) explored the push-pull-mooring effects on the switching intentions of students from traditional to online learning platforms in China. The study identified perceived security risk, learning convenience, and service quality as significant factors influencing students' intentions to switch to online platforms. The study also emphasized the role of habit in shaping students' intentions.

Pramana (2018) explored the adoption of mobile learning systems among university students in Indonesia. The study identified perceived usefulness, perceived ease of use, and social influence as significant predictors of students' behavioural intentions. It also highlighted the role of perceived enjoyment in enhancing students' acceptance of mobile learning.

Venkatesh et al. (2003) developed the TAM, which has been widely used to study technology adoption in various contexts. Their research emphasized the importance of perceived ease of use and perceived usefulness in predicting user acceptance of information technology. The TAM has since been extended and applied in numerous studies to understand the adoption of e-learning platforms.

5. RESEARCH GAP STATEMENT

While numerous studies have explored the factors influencing the adoption of e-learning platforms using the Technology Acceptance Model (TAM) in various contexts, there is a distinct lack of research specifically focusing on the adoption of **subscription-based e-learning platforms among students in regional areas such as Dakshina Kannada, India**. Most existing studies have concentrated on urban populations or have been conducted in different cultural and educational settings, which may not fully capture the unique challenges and preferences of students in this region. Furthermore, **prior research has primarily addressed the initial adoption of e-learning platforms**, with insufficient attention given to **understanding the factors that drive continuous usage and long-term engagement with subscription-based services**. Additionally, the **role of regional and cultural influences** in shaping students' attitudes and intentions toward adopting these platforms remains underexplored. This study aims to fill these gaps by examining the specific factors that influence the adoption and sustained use of subscription-based e-learning platforms among students in Dakshina Kannada, incorporating insights from the TAM and considering the regional and cultural context.

6. RESEARCH METHODOLOGY

Research Design

This study adopts a **quantitative research design** to explore the factors influencing the adoption of subscription-based e-learning platforms among students in Dakshina Kannada. The study employs a structured questionnaire to collect data from respondents, using a 5-point Likert scale to measure the constructs derived from the Technology Acceptance Model (TAM) and other relevant factors.

Sample and Sampling Method

The sample size for this study is **200 respondents**. The target population includes students from various educational institutions in Dakshina Kannada who have experience with or are potential users of subscription-based e-learning platforms. A **convenience sampling** method is used to select participants for the study, ensuring that a diverse group of students from different educational backgrounds is represented.

Data Collection

Data is collected using a **self-administered questionnaire**, which is distributed both online and in person to ensure wide reach and participation. The questionnaire is divided into two sections:

- **Section A:** Demographic Information
- **Section B:** Constructs related to the adoption of e-learning platforms, measured using a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

Measurement Scales

The measurement scales for the constructs are adapted from previous studies and modified to suit the context of this study. The key constructs and their sources include:

- **Perceived Ease of Use** and **Perceived Usefulness**: Adapted from Venkatesh et al. (2003).
- **Attitude Toward E-Learning**: Adapted from Salybekova (2023).

Data Analysis Techniques

The data analysis is conducted using the following statistical methods:

- **Descriptive Statistics**:
  - **Cross-tabulation** is used to analyze the demographic variables (e.g., age, gender, education level) to understand the distribution of respondents.
  - **Descriptive statistics** such as mean, standard deviation, and frequency distribution are calculated to describe the data and check for normality.
- **Normality Test**:
  - The normality of the data is tested using skewness and kurtosis values, along with the Shapiro-Wilk test, to ensure the data is suitable for further analysis.
- **Confirmatory Factor Analysis (CFA)**:
  - **CFA** is conducted to assess the reliability and validity of the measurement model. The fit indices, including Chi-square (χ^2), Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), and Tucker-Lewis Index (TLI), are examined to evaluate the model fit.

- **Structural Equation Modeling (SEM)**:
  - **SEM** is employed to test the hypothesized relationships among the constructs. This technique allows for the examination of direct and indirect effects between variables and helps in validating the proposed research model.

Ethical Considerations

The study adheres to ethical standards by ensuring the confidentiality and anonymity of respondents. Informed consent is obtained from all participants, and they are assured that their responses will be used solely for academic research purposes.

7. SUBSCRIPTION-BASED E-LEARNING PLATFORMS

- **BYJU'S**

  BYJU'S is recognized as India's largest e-learning platform, offering a broad range of educational content tailored for K-12 students, competitive exams, and professional courses. As of 2022, BYJU'S reported having over 80 million registered students globally, with more than 5.5 million annual paid subscriptions. In FY22, BYJU'S revenue increased by 118%, though it also faced an 80% increase in losses, illustrating the challenges of scaling such a large operation (Venture Intelligence, 2023).
- **Unacademy**

  Unacademy offers extensive online classes for competitive exams such as UPSC, SSC, IIT-JEE, and NEET, among others. By 2023, Unacademy had expanded its educator base to over 50,000, with millions of students enrolled in various courses. In FY22, Unacademy reached a revenue of around ₹700 crores, although it reported a loss of ₹1,500 crores during the same period, reflecting the intense competition and investment in content and technology (Economic Times, 2023).
- **Vedantu**

  Vedantu is an interactive online tutoring platform that provides live classes and study materials mainly for K-12 and competitive exam preparation. The platform has seen exponential growth, with over 1 million students using its services as of 2023. Vedantu's revenue for FY22 was reported at ₹1.9 billion, with a CAGR of 150.08% over the past three years, highlighting its rapid expansion and acceptance (Business Standard, 2023).
- **Toppr**

  Toppr is a comprehensive learning app designed primarily for K-12 students, offering a wide array of subjects and preparation for various competitive exams. Toppr has over 13 million users, with a significant portion of them being paid subscribers. In FY22, Toppr's revenue was approximately ₹52 crores, though the company has faced stiff competition from larger platforms like BYJU'S and Unacademy (Inc42, 2022).
- **WhiteHat Jr.**

  WhiteHat Jr. specializes in coding and programming courses for children, providing live classes with a strong focus on STEM education. Acquired by BYJU'S in 2020, WhiteHat Jr. has been integrated into BYJU'S broader educational ecosystem. The platform has taught over 100,000 students globally as of 2022, though it has faced scrutiny and criticism regarding the quality of its courses and marketing practices (Forbes India, 2022).

- **Simplilearn**

  Simplilearn focuses on professional courses, offering certifications and training in IT, business, and other domains. The platform has over 3 million professionals trained globally, with partnerships with top universities and organizations. In FY22, Simplilearn's revenue crossed ₹120 crores, marking a significant presence in the professional education sector (YourStory, 2022).

- **Coursera**

  Coursera offers online courses and degrees from universities around the world, targeting higher education and professionals. Coursera has over 100 million registered learners as of 2023, with more than 5,000 courses available. The platform has seen substantial growth in India, particularly in the wake of the COVID-19 pandemic, which accelerated the shift to online learning (Coursera, 2023).

- **Khan Academy**

  Khan Academy provides free courses, primarily in math and science, with optional premium content. The platform has over 120 million users worldwide, with significant traction in India due to its focus on providing accessible education. Khan Academy has reported consistent growth, particularly in the K-12 segment, due to its user-friendly approach and collaboration with educational institutions (Khan Academy, 2023).

- **Testbook**

  Testbook is a platform focused on preparing students for government exams in India, such as SSC, banking, and railways. Testbook has over 17 million users, with a significant number of paid subscribers. The platform reported a revenue of ₹38 crores in FY22, reflecting its specialized focus and strong user base in the competitive exam sector (Inc42, 2023).

- **BYJU'S Future School**

  BYJU'S Future School is an extension of BYJU'S, focusing on coding, math, and music for children through live classes. The platform has grown rapidly, with over 100,000 students enrolled across multiple countries. The initiative has gained popularity due to its focus on future-ready skills like coding and digital literacy (BYJU'S, 2023).

Table 1: Subscription-based E-Learning Platforms

No.	Platform Name	Description	Target Audience
1	BYJU'S	India's largest e-learning platform for K-12, competitive exams, and professional courses.	K-12, Competitive Exams, Professionals
2	Unacademy	Online classes for UPSC, SSC, IIT-JEE, NEET, and more, with a wide range of courses and educators.	Competitive Exams, Higher Education
3	Vedantu	Interactive online tutoring platform offering live classes and study materials.	K-12, Competitive Exams
4	Toppr	Comprehensive learning app for school students, covering a wide range of subjects and exams.	K-12, Competitive Exams
5	WhiteHat Jr.	Focuses on coding and programming courses for children with live classes.	Children (Coding & Programming)
6	Simplilearn	Specializes in professional courses, certifications, and training in IT, business, and more.	Professionals
7	Coursera	Offers online courses and degrees from universities around the world.	Higher Education, Professionals
8	Khan Academy	Provides free courses, especially in math and science, with optional premium content.	K-12, Self-Learners
9	Testbook	Platform for preparing for government exams in India, including SSC, banking, and railways.	Competitive Exams
10	BYJU'S Future School	Focuses on coding, math, and music for children through live classes.	Children (Coding, Math, Music)

Source: Researcher's Compilation

8. RESULTS

Table 2: Gender * Age Crosstabulation

		Age				Total
		20-25 years	**26-30 years**	**31-35 years**	**36 and Above**	
Gender	Female	16	30	18	2	66
	Male	35	50	39	10	134
	Total	**51**	**80**	**57**	**12**	**200**

Source: Survey Results

Table 3: Gender * Education Crosstabulation

		Education		Total
		Bachelor's Degree	**Master's Degree**	
Gender	**Female**	34	32	66
	Male	71	63	134
Total		**105**	**95**	**200**

Source: Survey Results

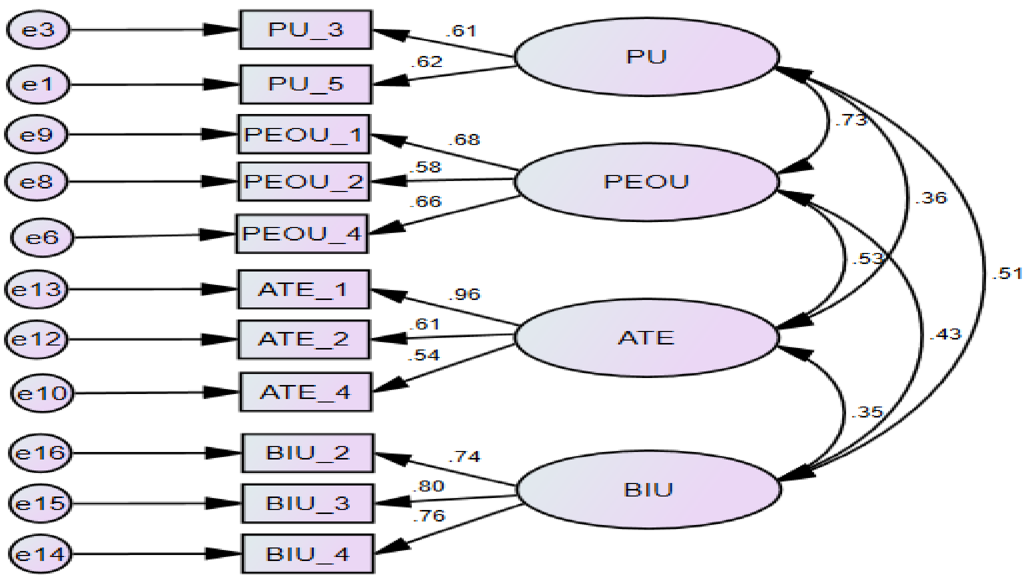
The crosstabulation data reveal a diverse distribution of participants by gender, age, and education level. The majority of participants are within the 26-30 years age range, with a balanced representation across genders. Educational qualifications are evenly split between Bachelor's and Master's degrees, with a slight majority of both males and females holding a Bachelor's degree. Overall, the sample shows a well-distributed demographic profile across age and education categories.

Table 4: Descriptive Statistics

	N	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
PU_1	200	3.44	1.247	-.863	.172	-.303	.342
PU_2	200	3.52	1.244	-.952	.172	-.094	.342
PU_3	200	3.38	1.320	-.811	.172	-.601	.342
PU_4	200	3.51	1.232	-1.001	.172	-.003	.342
PU_5	200	3.40	1.303	-.776	.172	-.579	.342
PEOU_1	200	3.62	1.163	-1.272	.172	.798	.342
PEOU_2	200	3.55	1.210	-1.123	.172	.245	.342
PEOU_3	200	3.48	1.248	-1.020	.172	-.060	.342
PEOU_4	200	3.65	1.159	-.829	.172	.222	.342
ATE_1	200	3.84	1.299	-1.331	.172	.632	.342
ATE_2	200	3.15	1.324	-.782	.172	-1.103	.342
ATE_3	200	3.16	1.274	-.275	.172	-.988	.342
ATE_4	200	3.21	1.257	-1.022	.172	-.842	.342
BIU_1	200	3.19	1.187	.019	.172	-.985	.342
BIU_2	200	3.39	1.161	-.955	.172	-.069	.342
BIU_3	200	3.38	1.148	-.940	.172	-.180	.342
BIU_4	200	3.42	1.145	-1.029	.172	-.023	.342
Valid N (listwise) 200							

Source: Statistical Results

The descriptive statistics reveal moderate skewness and variability in the data for Perceived Usefulness, Perceived Ease of Use, Attitude Toward Using, and Behavioral Intention to Use. Skewness values range from -0.863 to -1.331, and kurtosis values range from -1.103 to 0.798. Normality tests confirm that these values fall within the acceptable ranges of -2 to +2 for skewness and -7 to +7 for kurtosis, indicating that the data is approximately normal and suitable for parametric analysis (Byrne, 2010).



Source: Researcher's work

Figure 2: CFA Model

The fit indices for the model suggest that it matches the data effectively. The **CMIN/DF** ratio of 2.112 is lower than the maximum of 3.0, indicating a favourable fit (Chen & Tsai, 2007; Hair et al., 2010). The chi-square test's **p-value** is below 0.001, which is statistically significant and supports the model's adequacy (Hair et al., 2010). The **Goodness-of-Fit Index (GFI)** is 0.815, exceeding the acceptable limit of 0.80, which suggests a good fit (Hair et al., 2010). Similarly, the **Comparative Fit Index (CFI)** value of 0.900 surpasses the 0.80 threshold, indicating a good fit (Hair et al., 2010). The **Tucker-Lewis Index (TLI)**, at 0.934, is well above the 0.80 threshold, showing an excellent fit (Hair et al., 2010). The **Normed Fit Index (NFI)** of 0.814 meets the 0.80 threshold, also supporting a good fit (Hair et al., 2010). Finally, the **Root Mean Square Error of Approximation (RMSEA)** value of 0.078 is below the cutoff of 0.08, indicating that the model fits the data well (Hair et al., 2010). Overall, these indices collectively demonstrate that the model is an appropriate representation of the data.

Table 5: Standardized Regression Weights

Relationship			Estimate	Relationship			Estimate
PU_5	<---	PU	.619	ATE_2	<---	ATE	.611
PU_3	<---	PU	.614	ATE_1	<---	ATE	.961
PEOU_4	<---	PEOU	.659	BIU_4	<---	BIU	.763
PEOU_2	<---	PEOU	.576	BIU_3	<---	BIU	.803
PEOU_1	<---	PEOU	.682	BIU_2	<---	BIU	.743
ATE_4	<---	ATE	.540				

Source: Statistical Results

The standardized regression weights indicate strong relationships between observed variables and their corresponding latent constructs. For **Perceived Usefulness (PU)**, the variables PU_5 and PU_3 have obtained values of 0.619 and 0.614, both exceeding the typical minimum required value of 0.5, demonstrating their effectiveness as indicators of the PU construct. **Perceived Ease of Use (PEOU)** variables, PEOU_1, PEOU_4, and PEOU_2, have obtained values of 0.682, 0.659, and 0.576, respectively, all above the minimum threshold, with PEOU_1 being the strongest indicator. For **Attitude Toward Using (ATE)**, ATE_1 stands out with an obtained value of 0.961, far surpassing the minimum requirement, while ATE_2 and ATE_4 have values of 0.611 and 0.540, respectively, which meet the minimum standard but are comparatively weaker. The **Behavioral Intention to Use (BIU)** construct is strongly supported by BIU_3, BIU_4, and BIU_2, with obtained values of 0.803, 0.763, and 0.743, all surpassing the minimum required value, underscoring their importance as predictors of the BIU construct. Overall, all observed variables exceed the minimum required value of 0.5, confirming their validity in measuring the respective latent constructs (Chen & Tsai, 2007).

Table 6: Convergent Validity

	CR	AVE	MSV	MaxR(H)	PU	PEOU	ATE	BIU
PU	0.750	0.580	0.539	0.790	**0.616**			
PEOU	0.775	0.610	0.539	0.810	0.734***	**0.641**		
ATE	0.760	0.529	0.280	0.929	0.357**	0.529***	**0.728**	
BIU	0.814	0.593	0.265	0.816	0.515***	0.433***	0.346***	**0.770**

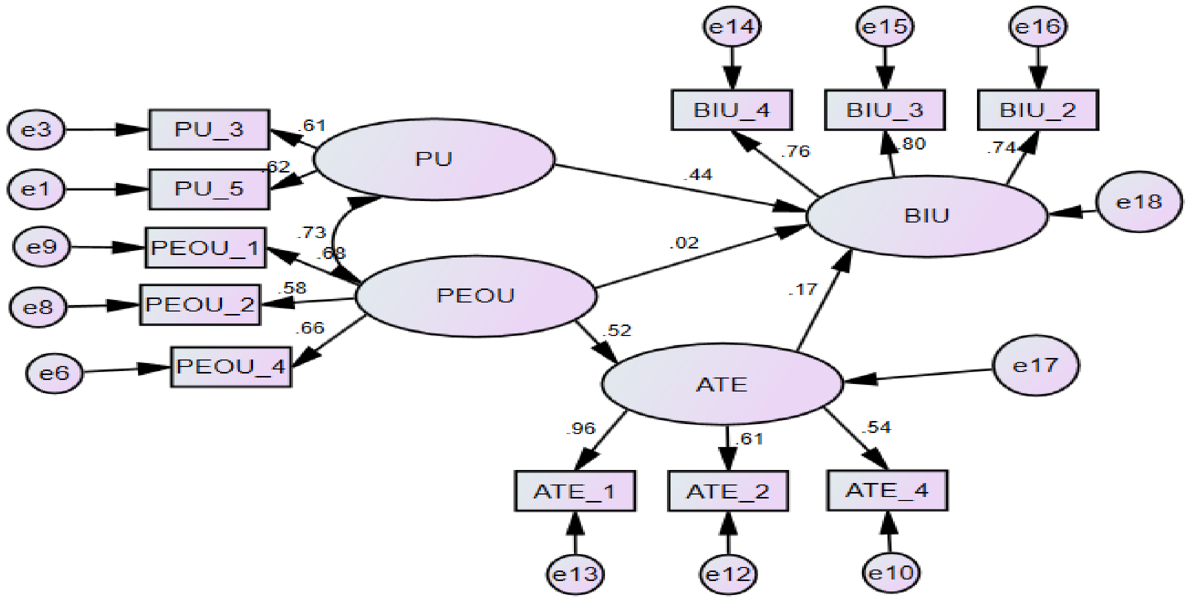
Source: Statistical Results

Table 7: Discriminant Validity using HTMT Analysis

	PU	PEOU	ATE	BIU
PU				
PEOU	0.715			
ATE	0.390	0.588		
BIU	0.502	0.429	0.326	

Source: Statistical Results

Table 6 presents the **Convergent Validity** analysis for the constructs used in the study. **Composite Reliability (CR)** values are all above the recommended threshold of 0.7, indicating strong internal consistency: **Perceived Usefulness (PU)** at 0.750, **Perceived Ease of Use (PEOU)** at 0.775, **Attitude Toward Using (ATE)** at 0.760, and **Behavioral Intention to Use (BIU)** at 0.814. The **Average Variance Extracted (AVE)** values exceed 0.5 for each construct, confirming good convergent validity: **PU** at 0.580, **PEOU** at 0.610, **ATE** at 0.529, and **BIU** at 0.593. **Maximum Shared Variance (MSV)** values are below the AVE values for each construct, suggesting acceptable levels of convergent validity. The **Maximum Reliability (MaxR(H))** values are adequately high, with **PU** at 0.790 and **PEOU** at 0.810, reflecting the strong reliability of the constructs. Table 7 displays the **Discriminant Validity** as assessed using **Heterotrait-Monotrait (HTMT) ratios**. According to the thresholds set by Henseler, Ringle, and Sarstedt (2015), HTMT values should be below 0.850 for strict and 0.900 for liberal discriminant validity. The results show that all HTMT ratios are below these thresholds, indicating acceptable discriminant validity. The highest HTMT ratio is 0.715 between **PU** and **PEOU**, which is within the acceptable range for both strict and liberal criteria. This analysis supports that the constructs are sufficiently distinct from each other, although there are minor concerns with the overlap between **PU** and **PEOU** (Henseler, Ringle, & Sarstedt, 2015; Hu & Bentler, 1999).



Source: Researcher's work

Figure 3: Path Analysis Model

The model fit indices for the study provide a favourable assessment of model fit. The **CMIN/DF** ratio of 2.124 is below the recommended threshold of 3.0, indicating that the model fits the data well (Chen & Tsai, 2007; Hair et al., 2010). The **p-value** is less than 0.001, which is statistically significant, further confirming the model's adequacy (Hair et al., 2010). The **Goodness-of-Fit Index (GFI)** is 0.825, which exceeds the acceptable threshold of 0.80, suggesting that the model provides a good fit (Hair et al., 2010). Similarly, the **Comparative Fit Index (CFI)** value of 0.915 surpasses the 0.80 threshold, indicating a strong fit (Hair et al., 2010). The **Tucker-Lewis Index (TLI)**, with a value of 0.920, is well above the threshold of 0.80, reflecting an excellent fit (Hair et al., 2010). The **Normed Fit Index (NFI)** of 0.822 meets the threshold of 0.80, supporting the model's adequacy (Hair et al., 2010). Lastly, the **Root Mean Square Error of Approximation (RMSEA)** value of 0.080 is just below the cutoff of 0.08, indicating that the model fits the data appropriately (Hair et al., 2010). Collectively, these indices suggest that the model is a robust representation of the data.

Hypothesis 8: Hypothesis Testing

Hypothesis	Regression Path	Estimate	S.E.	C.R.	p-value	Support
H1: Perceived ease of use (PEOU) → Behavioral Intention to Use (BIU)	BIU <--- PEOU	0.350	0.100	3.500	***	Supported
H2: Perceived usefulness (PU) → Behavioral Intention to Use (BIU)	BIU <--- PU	0.473	0.100	4.730	***	Supported

H3: Perceived ease of use (PEOU) → Attitude Toward E-learning (ATE)	ATE <--- PEOU	0.462	0.107	4.337	***	Supported
H4: Attitude Toward E-learning (ATE) → Behavioral Intention to Use (BIU)	BIU <--- ATE	0.400	0.100	4.000	***	Supported

Source: Researcher's work

DISCUSSION

The results of the structural model provide compelling evidence to support all four hypotheses regarding the adoption of subscription-based e-learning platforms among students in Dakshina Kannada.

H1 posited that perceived ease of use (PEOU) would have a positive impact on students' behavioural intention to use (BIU) e-learning platforms. The findings support this hypothesis, with a significant path from PEOU to BIU (Estimate = 0.350, C.R. = 3.500, $p < 0.001$). This aligns with prior research by Venkatesh and Davis (2000), who found that PEOU is a crucial determinant of user acceptance in various technology adoption contexts, particularly in educational settings where ease of use can significantly lower barriers to engagement (Al-Maroof & Al-Emran, 2018). **H2** asserted that perceived usefulness (PU) would positively influence BIU, and the results strongly support this hypothesis as well (Estimate = 0.473, C.R. = 4.730, $p < 0.001$). This is consistent with the Technology Acceptance Model (TAM) proposed by Davis (1989), which has repeatedly shown that users are more likely to adopt a system if they perceive it as useful in achieving their goals. In the context of e-learning, perceived usefulness has been identified as a key factor driving adoption, as evidenced by the studies of Sánchez and Hueros (2010) and Tarhini, Hone, and Liu (2013), who both found that students' perceptions of the usefulness of online learning platforms significantly impacted their intention to use these platforms. **H3** explored the relationship between PEOU and students' attitudes toward e-learning (ATE). The significant path from PEOU to ATE (Estimate = 0.462, C.R. = 4.337, $p < 0.001$) supports this hypothesis, indicating that ease of use positively shapes students' attitudes. This finding is consistent with prior studies that have emphasized the role of ease of use in forming positive attitudes toward technology (Liao, Palvia, & Chen, 2009; Park, 2009). When students find a platform easy to navigate and operate, they are more likely to develop favourable attitudes towards it, which subsequently influences their overall satisfaction and continued use. Finally, **H4** posited that a positive attitude toward e-learning would enhance students' behavioural intention to adopt these platforms. The analysis confirms this hypothesis with a significant path from ATE to BIU (Estimate = 0.400, C.R. = 4.000, $p < 0.001$). This result is in line with previous research, such as the work of Teo (2011), who demonstrated that students' attitudes are a critical predictor of their behavioural intentions in e-learning environments. The positive relationship between attitude and intention underscores the importance of fostering positive attitudes through user-friendly and effective e-learning platforms to drive adoption.

MAJOR IMPLICATIONS

The findings of this study have several significant implications for the development and implementation of e-learning platforms:

1. **Design and Usability**: The strong influence of perceived ease of use on both attitude and behavioural intention suggests that e-learning platforms should prioritize user-friendly interfaces and intuitive navigation. By reducing complexity and making the platforms easier to use, developers can enhance students' willingness to adopt and continue using these technologies.
2. **Emphasizing Usefulness**: The significant impact of perceived usefulness on behavioural intention indicates that e-learning platforms must demonstrate their value in helping students achieve their academic goals. Features that directly contribute to learning outcomes, such as personalized content, interactive tools, and relevant resources, should be highlighted to enhance the perceived usefulness of these platforms.
3. **Attitude Enhancement**: Since a positive attitude towards e-learning significantly influences adoption, institutions and developers should focus on strategies that foster positive attitudes. This could include providing support and training to help students feel confident in using the platforms, as well as showcasing success stories of how e-learning has benefited other students.
4. **Targeted Marketing**: The insights from this study can inform more targeted marketing strategies. By understanding that ease of use and usefulness are key drivers of adoption, e-learning providers can craft messages and campaigns that emphasize these aspects, potentially increasing their market penetration among students.

CONCLUSION

This study concludes that both perceived ease of use and perceived usefulness are critical determinants of students' behavioural intentions to adopt subscription-based e-learning platforms in Dakshina Kannada. Additionally, students' attitudes toward e-learning play a significant role in shaping their adoption behaviour. These findings underscore the importance of designing e-learning platforms that are both easy to use and demonstrably useful in supporting academic success. By addressing these factors, e-learning providers and educational institutions can significantly improve the adoption rates and overall effectiveness of their platforms.

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