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RESEARCH ARTICLE

MODELLING COLLEGE STUDENTS' INTENTION TO USE GENERATIVE AI-BASED ENGLISH LANGUAGE LEARNING APPLICATIONS: AN INTEGRATED TAM-TPB APPROACH

Pradeesh N.M[1], Navya A.H[2] and Samanway Krishnan[3]

1.Associate Professor of Commerce, C.K.G. Memorial Government College, Perambra, Kozhikode, Kerala, India.
2.Assistant Professor of Commerce, Panampilly Memorial Government College Chalakkudy, Thrissur, Kerala, India.
3.Assistant Professor of Commerce, RD College of Commerce and Professional Studies, Perundurai, Tamil Nadu,India.

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Abstract

The progression of Generative Artificial Intelligence (GAI) has revolutionized English language learning. It has ensured personalized, interactive and accessible learning experiences. This study examines the factors influencing college students intention to use generative AI based English language learning applications. The present study integrates the Technology Acceptance Model (TAM) and Theory of Planned Behavior (TPB). The study explores the effects of perceived usefulness, perceived ease of use, attitude, subjective norm, and perceived behavioral control on students' behavioural intention. A cross sectional descriptive research design was applied. The primary data were collected through a structured questionnaire circulated to undergr aduate and postgraduate students in various Arts and Science Colleges. Structural Equation Modeling (SEM) was employed to test the proposed conceptual model utilizing 267 responses. It is found that Perceived usefulness and perceived ease of use significantly and positively influenced students' attitudes toward using Generative AI based English language applications. The study also shows that attitude, subjective norm, and perceived behavioral control significantly influenced behavioural intention of students. The structural model demonstrated 69.5% of the variance in attitude and 56.9% of the variance in behavioural intention. The findings show that the integrated TAM and TPB framework provides a rigorous explanation of college students' acceptance of generative AI based English language learning applications.

Corresponding Author:- Pradeesh N.M
Address:-Associate Professor of Commerce, C.K.G. Memorial Government College, Perambra, Kozhikode, Kerala, India.

Introduction:-

Higher education institutions increasingly need to adopt, and continuously improve educational technologies to enhance the efficiency of teaching and learning (Mogul & Shah, 2022). Beyond restructuring learning experiences, educational technologies support to the overall quality of education. It promotes innovation, accessibility, flexibility, and student engagement (Alenezi, 2023). The exstensive use of smart phones, tablets, artificial intelligence, and big data analytics has expedited the transition from traditional learning environments toward smart learning ecosystems (Hamal et al., 2022). Higher education institutions are increasingly integrating digital technologies in all major areas of teaching and learning such as course delivery, student support services, curriculum development, and assessment (Sharma et al., 2020). When properly implemented, these technologies can create interactive and learner centred educational environments that improve learning efficiency, student engagement, and academic performance (Ravichandran & Shanmugam, 2023).

Effective translation of technology into meaningful educational outcomes requires appropriate technological infrastructure, institutional support, faculty preparedness, and relevant pedagogical strategies. Without these supportive conditions, the adoption of educational technologies may not yield the expected results in teaching and learning (Ahmad et al., 2023). Consequently, understanding the factors that influence the acceptance and effective use of educational technologies has become a significant area of inquiry for teachers, higher education institutions, and policymakers. Such insights are essential for formulating appropriate strategies and institutional policies that can optimize the educational benefits arising from the ongoing digital transformation (Liu et al., 2020). Among the technological innovations transforming the educational landscape, artificial intelligence (AI) has emerged as one of the most significant developments.

The generative artificial intelligence (GAI) technologies have gained significant attention from researchers, and international organizations because of their power to transform traditional teaching and learning practices (Chen et al., 2024). Exploring the educational implications of GAI requires a clear distinction between generative AI and traditional forms of artificial intelligence, especially in terms of their underlying capabilities, functions, and applications (Kooli & Yusuf, 2024). Conventional AI systems are generally developed to analyse data, identify patterns, make predictions, and automate predefined tasks. GAI is primarily described by its ability to create new content in response to user provided prompts. GAI extends beyond merely processing or interpreting existing knowledge by creating context specific and increasingly sophisticated outputs (Cong-Lem et al., 2024). The growing educational applications of GAI show its potential to transform multiple dimensions of higher education. These technologies are increasingly being employed in personalized learning, educational content development, automated assessment, language learning, curriculum design, and administrative activities. By enabling personalized learning, providing timely feedback, and supporting educators in content development, Generative Artificial Intelligence (GAI) can potentially improve teaching effectiveness and enhance student engagement. The integration of GAI into higher education is increasingly regarded not simply as a technological advancement but as a substantial transformation that may shape the future direction of educational systems (Wang et al., 2024).

Research Objectives:-

1. To examine the effects of Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) on college students' attitudes toward using generative AI based English language learning applications.
2. To analyze the influence of Attitude, Subjective Norms, and Perceived Behavioral Control (PBC) on college students' behavioral intention to use generative AI-based English language learning Apps.

Literature Review:-

Theoretical framework and hypothesis development:-

Technology Acceptance Model:-

Fast paced technological advancements have fundamentally transformed industries. It has disrupted the traditional business models and meanwhile, generated new opportunities for innovative products and services (Lai, 2006). Consumers' adoption of emerging technologies is affected by a variety of factors. It includes technological accessibility, convenience, perceived usefulness, ease of use, security, and individual requirements. As a result, identifying the factors that influence technology adoption has become a significant area of research (Meuter et al., 2000). The Technology Acceptance Model (TAM) is one of the key theoretical frameworks for understanding technology adoption. It is initially developed by Davis (1986) and subsequently empirically validated by Davis (1989). TAM was developed to explain and predict individuals' acceptance and use of information systems across different technological settings. The model mainly focuses on two key cognitive beliefs such as Perceived

Usefulness (PU) and Perceived Ease of Use (PEOU). Perceived usefulness refers to the extent to which an individual believes that using a particular technology will improve task performance. Perceived ease of use represents the extent to which an individual perceives that using the technology will require minimal effort (Davis, 1989). Within the TAM framework, these two beliefs are central to determining users' attitudes toward a technology. These two factors subsequently influence their behavioural intention to use it. The theoretical foundation of TAM is closely linked with the concepts of attitude and behavioural intention proposed by Fishbein and Ajzen (1975). Their framework recommends that human behaviour is mainly determined by behavioural intentions. Attitudes indicate an individual's favourable or unfavourable evaluation of a particular behaviour. TAM recommends that individuals who perceive a technology as useful and easy to use are more likely to develop positive attitudes toward it. The attitude in turn strengthens their intention to adopt it. Davis (1989) further extended TAM by incorporating five major constructs such as perceived usefulness, perceived ease of use, attitude toward use, intention to use, and actual usage. Subsequently, Venkatesh and Davis (2000) extended the model by highlighting the role of external variables, including system characteristics and users' prior experience, which may indirectly influence technology acceptance by shaping perceptions of usefulness and ease of use. TAM has been extensively employed to investigate the acceptance of educational technologies such as e-learning platforms, mobile learning applications, learning management systems, and online learning environments. Researchers have combined TAM with other theoretical perspectives to enhance its explanatory capacity. Wang et al. (2023) combined the Task-Technology Fit (TTF) model with TAM to analyze university students' behavioural intentions to use emerging online learning platforms.

Theory of Planned Behaviour:-

The Theory of Planned Behavior (TPB), developed by Ajzen (1991), is one of the most widely applied theoretical frameworks. TPB is used for explaining and predicting human behaviour across varied fields such as psychology, behavioural sciences, healthcare, environmental studies, and education (Kwon & Silva, 2020). The theory proposes that behavioural intention is primarily determined by three factors such as attitude, subjective norm, and perceived behavioural control (PBC) (Ajzen, 1991). These three determinants emerge from three corresponding categories of beliefs. Behavioural beliefs influence attitude by reflecting an individual's expectations regarding the expected outcomes of engaging in a specific behaviour. Normative beliefs shape subjective norms. It captures perceived social expectations from important referent groups such as family members, friends, teachers, and peers. Control beliefs contribute to perceived behavioural control. It reflects an individual's perceptions of the resources, opportunities, capabilities, and constraints associated with engaging in the behaviour (Ajzen, 1991). These beliefs are formed through previous experiences, and contextual circumstances. Attitude encompasses cognitive, affective, and behavioural predispositions. It reflects what individuals believe about the behaviour, how they feel about it, and their inclination to perform it (Hoyer et al., 2012). When individuals perceive a behaviour as useful or enjoyable, they are more likely to develop a favourable attitude toward it. Subjective norm represents an individual's perception of social pressure to perform or avoid a particular behaviour (Ajzen, 2005). It is primarily influenced by normative beliefs concerning the expectations of significant others and the individual's motivation to comply with those expectations. Thus, individuals are more inclined to engage in a particular behaviour when they believe that important people in their social environment encourage the behaviour.

Perceived behavioural control refers to an individual's perception of the ease or difficulty associated with performing a particular behaviour. It reflects their assessment of the resources, skills, opportunities, and constraints involved (Ajzen, 1991). Ajzen (2002) emphasized the relevance of perceived self-efficacy, a concept derived from Bandura's (1999) work. Self-efficacy reflects an individual's confidence in their ability to perform a specific behaviour. Higher degrees of perceived behavioural control and self-efficacy can strengthen behavioural intentions. TPB has been widely used in educational research to explain students' adoption of educational technologies. Previous empirical research has shown that perceived behavioural control can largely influence university students' intentions to participate in technology supported educational activities (Lung-Guang, 2019; Pan et al., 2023). Ajzen (1985) recognized that contextual constraints and unforeseen circumstances may prevent individuals from translating their behavioural intentions into actual actions. Despite this limitation, TPB continues to serve as an established framework for explaining behavioural intentions. Its emphasis on individual attitudes, perceived social expectations, and perceived control makes it particularly relevant for examining students' acceptance of emerging educational technologies. In the context of generative artificial intelligence (GAI), these dimensions can help explain how students' evaluations of GAI, social influences from peers and educators, and perceived ability to use such technologies influences their intention to adopt GAI based educational applications.

Although TAM has been extensively employed to explore technology acceptance in educational settings, the integration of TAM and TPB for examining students' behavioural intentions to adopt AI based educational applications remains relatively unexplored. The rapid advancement of GAI in higher education have increased the need to understand factors that influence students' acceptance of these emerging technologies (Wang et al., 2025). Integrating TAM with TPB can therefore provide a more comprehensive theoretical perspective. It brings together technology specific perceptions such as perceived usefulness and perceived ease of use, with behavioural and social determinants. Such an integrated framework can offer a stronger basis for explaining students' behavioural intentions toward AI based educational applications.

Research Hypotheses:-

The following are the research hypothesis:-

H1: Perceived usefulness positively influences college students' attitude toward using generative AI based English language learning applications.

H2: Perceived ease of use positively influences college students' attitude toward using generative AI based English language learning applications.

H3: College students' attitude toward using generative AI based English language learning applications positively influences their behavioural intention to use these applications.

H4: Subjective norms positively influence college students' behavioural intention to use generative AI based English language learning applications.

H5: Perceived behavioral control positively influences college students' behavioral intention to use generative AI based English language learning applications

Methodology and Data Collection:-

Research Design:-

This study adopted an integrated Technology Acceptance Model and Theory of Planned Behaviour framework to explore college students' intention to use Generative AI based English language learning Apps. This study employed a quantitative research approach. A structured questionnaire was designed by adapting validated measurement items from previous studies. Primary data were collected from the selected respondents. The data were analysed using the Statistical Package for the Social Sciences (SPSS) and Analysis of Moment Structures (AMOS). SPSS was utilized for data screening, descriptive statistics, and reliability analysis. AMOS was applied to validate the measurement model and test the structural model through Structural Equation Modelling (SEM). The proposed hypotheses were examined by analysing the relationships among the latent constructs. The adequacy of the measurement and structural models was evaluated using model fit indices such as Goodness of Fit Index (GFI), Comparative Fit Index (CFI), Tucker Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA).

Data Collection:-

A cross sectional descriptive research design was adopted to investigate college students' intention to use Generative AI based English language learning Apps. Primary data were collected from undergraduate (UG) and postgraduate (PG) students enrolled in higher education institutions in Thrissur District using a structured questionnaire. Each student constituted a sampling unit. A combination of convenience sampling and judgmental sampling techniques was employed to select the respondents. A total of 281 questionnaires were collected, of which 14 were excluded due to incomplete or invalid responses. Finally, 267 valid questionnaires were retained for the final analysis. This sample size is considered sufficient for conducting testing the proposed research model.

Results and Discussion:-

Table 1. Demographic Profile of the Respondents

Variable	**Category**	**Frequency (n)**	**Percentage (%)**
Gender	Male	107	40.1
	Female	160	59.9
Programme	Undergraduate	195	73.0
	Postgraduate	72	27.0
Discipline	Arts	72	27.0
	Science	88	33.0
	Commerce and Management	107	40.1

Medium of School Education	Malayalam	215	80.5
	English	52	19.5
Residence	Rural	208	77.9
	Urban	59	22.1
Total		267	100

The demographic profile shows that the study included a total number of 267 respondents. It consists of 160 female (60%) and 107 male (40%) students. Majority of them are female students. The majority of participants were undergraduate students (73%). The remaining 27% of the students were enrolled in postgraduate programmes. Regarding academic discipline, Commerce and Management students constituted the largest group (40.1%). It is followed by Science (33.0%) and Arts (27.0%). The study provides representation from the major streams of higher education. A substantial majority of respondents (80.5%) had completed their school education through the Malayalam medium.19.5% had studied in the English medium. Most participants (77.9%) belonged to rural areas.22.1% of the students were from urban area. The sample represents a diverse group of undergraduate and postgraduate students across different academic disciplines. It makes appropriate for examining students' intention to use Generative AI based English language learning Apps.

Table 2. Discriminant Validity Assessment Using the Fornell–Larcker Criterion

Construct	PU	PEOU	SN	PBC	ATT	INT
PU	**0.796**					
PEOU	0.720	**0.840**				
SN	0.678	0.457	**0.847**			
PBC	0.143	0.008	0.048	**0.857**		
ATT	0.567	0.327	0.421	0.180	**0.807**	
INT	0.505	0.293	0.295	0.111	0.536	**0.709**

Note: Diagonal values (shown in **bold**) represent the square root of the AVE, while the off diagonal values represent the correlations between constructs.

Discriminant validity was tested using the Fornell-Larcker criterion (Fornell & Larcker, 1981). According to this criterion, discriminant validity is established when the square root of the AVE for each construct is higher than its correlations with the other constructs. As shown in Table 2, the square roots of AVE were 0.796 for Perceived Usefulness (PU), 0.840 for Perceived Ease of Use (PEOU), 0.847 for Subjective Norm (SN), 0.857 for Perceived Behavioural Control (PBC), 0.807 for Attitude (ATT), and 0.709 for Behavioural Intention (INT). All these values were higher than the corresponding correlations with other constructs. It is found that all constructs satisfied the Fornell-Larcker criterion. It confirms satisfactory discriminant validity. This indicates that each construct is sufficiently distinct from the others and measures a unique aspect of students' acceptance of generative AI for English language learning. It is concluded that the measurement model is suitable for further structural model analysis.

Table 3. Multicollinearity Diagnostics

Predictor	Tolerance	VIF
Perceived Usefulness	0.593	1.687
Perceived Ease of Use	0.593	1.687
Subjective Norm	0.635	1.575
Perceived Behavioral Control	0.998	1.002
Attitude	0.635	1.574

Multicollinearity of the data was examined using the Tolerance and Variance Inflation Factor (VIF). According to Hair et al. (2022), tolerance values greater than 0.10 and VIF values below 5 indicate that multicollinearity is not a serious concern. Field (2018) suggested that VIF values substantially below 10.00 and tolerance values above 0.10 indicate acceptable levels of independence among the predictor variables. For the model predicting Attitude, the tolerance values for Perceived Usefulness and Perceived Ease of Use were both 0.593. VIF values were 1.687. Both values fall well within the acceptable limits. It indicates that the two predictor variables are not highly correlated and each contributes unique explanatory information. For the model predicting Behavioural Intention, the tolerance values ranged from 0.635 to 0.998. VIF values ranged from 1.002 to 1.575. It also indicates the absence of multicollinearity among Subjective Norm, Perceived Behavioural Control, and Attitude.

Table 4. Autocorrelation Test (Durbin–Watson)

Dependent Variable	**Predictors**	**Durbin–Watson**	**Recommended Range**
Attitude	Perceived Usefulness, Perceived Ease of Use	**2.139**	1.50–2.50
Behavioral Intention	Subjective Norm, Perceived Behavioral Control, Attitude	**1.748**	1.50–2.50

The independence of residuals was assessed using the Durbin-Watson statistic. Values between 1.50 and 2.50 are commonly regarded as acceptable limit. For the model predicting Attitude, the Durbin-Watson statistic was 2.139.It indicates an excellent level of independence among the residuals. The model predicting Behavioural Intention produced a Durbin-Watson value of 1.748. It also falls within the recommended range. These findings indicate that the residuals of both regression models are independent and that autocorrelation is not present.

Table 5. Convergent Validity and Reliability Assessment

Factor	Measure	Standardized Loading	p-value	AVE	Cronbach's α	Composite Reliability (CR)
Perceived Usefulness (PU)	PU1	0.787	<0.001	0.634	0.876	0.874
	PU2	0.828	<0.001			
	PU3	0.803	<0.001			
	PU4	0.762	<0.001			
Perceived Ease of Use (PEOU)	PEOU1	0.850	<0.001	0.706	0.905	0.906
	PEOU2	0.836	<0.001			
	PEOU3	0.842	<0.001			
	PEOU4	0.830	<0.001			
Subjective Norm (SN)	SN1	0.832	<0.001	0.717	0.917	0.910
	SN2	0.853	<0.001			
	SN3	0.895	<0.001			
	SN4	0.844	<0.001			
Perceived Behavioral Control (PBC)	PBC1	0.868	<0.001	0.734	0.916	0.917
	PBC2	0.870	<0.001			
	PBC3	0.868	<0.001			
	PBC4	0.814	<0.001			
Attitude (ATT)	ATT1	0.823	<0.001	0.651	0.884	0.881
	ATT2	0.775	<0.001			
	ATT3	0.821	<0.001			
	ATT4	0.801	<0.001			
Behavioral Intention (INT)	INT1	0.721	<0.001	0.503	0.809	0.802
	INT2	0.721	<0.001			
	INT3	0.717	<0.001			
	INT4	0.686	<0.001			

The convergent validity and reliability of the measurement model were assessed. The standardized factor loadings, Average Variance Extracted (AVE), Cronbach's alpha, and Composite Reliability (CR) are applied. All standardized factor loadings exceeded the recommended threshold of 0.70 .It is statistically significant ($p < 0.001$). It indicates that the observed indicators adequately represented their respective latent constructs. The AVE values ranged from 0.503 to 0.734. It exceeds the recommended minimum value of 0.50. It confirms adequate convergent validity. Furthermore, Cronbach's alpha values ranged from 0.80 to 0.92. The Composite Reliability values ranged from 0.802 to 0.917. Both of which are above the recommended threshold of 0.70. These findings demonstrate that the constructs possess satisfactory internal consistency reliability and convergent validity. It further suggests that the measurement model is reliable and suitable for subsequent structural model analysis.

Table 6. Structural Model Results and Hypothesis Testing

Hypothesis	Relationship	Unstandardized Coefficient (β)	Standardized Coefficient (β)	S.E.	C.R.	p-value	Decision
H1	Perceived Usefulness (PU) → Attitude (ATT)	0.649	0.567	0.093	6.970	<0.001	Supported
H2	Perceived Ease of Use (PEOU) → Attitude (ATT)	0.332	0.327	0.075	4.399	<0.001	Supported
H3	Subjective Norm (SN) → Behavioral Intention (INT)	0.227	0.295	0.054	4.236	<0.001	Supported
H4	Perceived Behavioral Control (PBC) → Behavioral Intention (INT)	0.075	0.111	0.037	2.034	0.042	Supported
H5	Attitude (ATT) → Behavioral Intention (INT)	0.446	0.536	0.065	6.912	<0.001	Supported

Table 7.Coefficient of Determination (R^2)

Endogenous Construct	R^2	Variance Explained
Attitude (ATT)	0.695	69.5%
Behavioral Intention (INT)	0.569	56.9%

The result of the study shows that perceived usefulness significantly and positively influenced attitude (β = .567, B = 0.649, CR = 6.970, $p < .001$). It supports H1. The students who perceive generative AI applications as useful for improving their English language learning are more likely to develop favourable attitudes toward using these technologies. Perceived usefulness arisen as the strongest predictor. It highlights the significance of the perceived educational benefits of generative AI in shaping students' evaluations. Perceived ease of use also exerted a significant positive effect on attitude (β = .327, B = 0.332, CR = 4.399, $p < .001$). It supported H2. The result suggests that students who perceive generative AI applications as easy to understand and operate tend to develop more favourable attitudes toward their use. Attitude significantly and positively influenced behavioural intention (β = .536, B = 0.446, CR = 6.912, $p < .001$), providing strong support for H3. This result indicates that students with more favourable attitudes toward generative AI exhibit stronger intentions to adopt these applications for English language learning. Attitude emerged as the strongest predictor of behavioural intention. This confirms its central role in the integrated TAM–TPB framework. Subjective norm had a significant positive effect on behavioural intention (β = .295, B = 0.227, CR = 4.236, $p < .001$), supporting H4. The perceived social influence from teachers, classmates, peers, and other significant individuals enhances students' intention to use generative AI applications. Perceived behavioural control also positively influenced behavioural intention (β = .111, B = 0.075, CR = 2.034, p = .042), thereby supporting H5. Despite the relationship being statistically significant, the standardized coefficient indicates that perceived behavioural control had the weakest effect among the predictors of behavioural intention. This finding suggests that students' confidence in their ability, knowledge, and available resources to use generative AI contributes positively to adoption intention.

Perceived usefulness and perceived ease of use jointly explained 69.5% of the variance in attitude (R^2 = .695). It indicates that the TAM constructs explained a substantial proportion of students' evaluations of generative AI based English language learning applications. Attitude, subjective norm, and perceived behavioural control collectively explained **56.9%** of the variance in behavioural intention (R^2 = .569). It suggests that the integrated model possesses strong explanatory capability in predicting students' intention to adopt generative AI applications. All hypothesized relationships were statistically significant. Perceived usefulness emerged as the strongest determinant of attitude and the attitude was identified as the most significant predictor of behavioural intention.

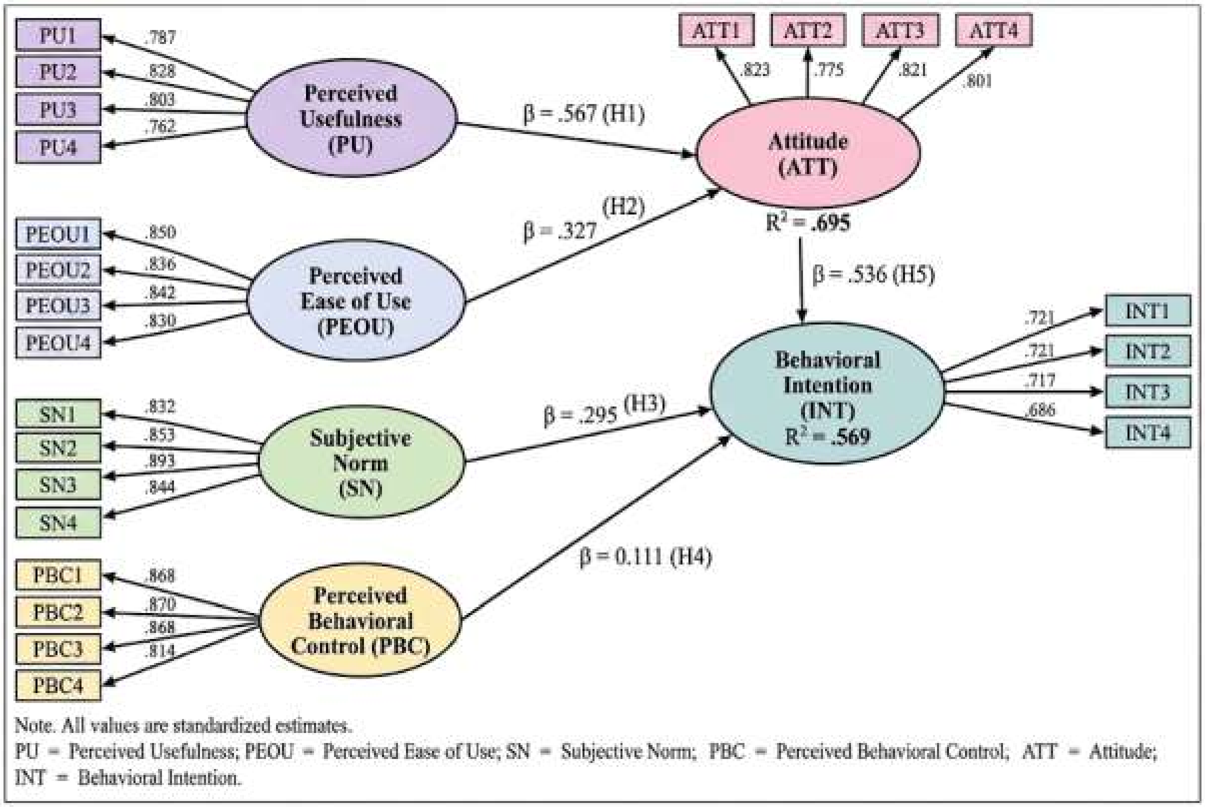

Fig 1: Structural Equation Model

Table 8. Model Fit Indices of the Structural Model

Fit Index	Obtained Value	Recommended Criterion	Interpretation	References
CMIN/DF (χ^2/df)	2.208	< 3.00 (acceptable); < 5.00 (permissible)	Good Fit	Joseph F. Hair Jr. et al. (2022); Barbara M. Byrne (2016)
GFI	0.858	≥ 0.90 (good); ≥ 0.85 (acceptable)	Acceptable Fit	Barbara M. Byrne (2016)
AGFI	0.823	≥ 0.80	Acceptable Fit	Barbara M. Byrne (2016)
IFI	0.935	≥ 0.90	Good Fit	Joseph F. Hair Jr. et al. (2022)
CFI	0.935	≥ 0.90	Good Fit	Joseph F. Hair Jr. et al. (2022)
RMR	**0.076**	≤ 0.08	Acceptable Fit	Barbara M. Byrne (2016)
RMSEA	**0.067**	≤ 0.08 (acceptable); ≤ 0.06 (good)	Acceptable Fit	Roger E. Bagozzi & Yi You; Joseph F. Hair Jr. et al. (2022)

The overall fitness of the proposed structural model was evaluated using various goodness of fit indices. The obtained CMIN/DF value was 2.208.It is below the recommended threshold of 3. It indicates a good level of model fit. The Goodness of Fit Index (GFI) is 0.858. Although this value is marginally below the ideal benchmark of 0.90, it exceeds the commonly accepted minimum level of 0.85.GFI indicates an acceptable level of overall model fit. The Adjusted Goodness of Fit Index (AGFI) is 0.823. It is greater than the recommended minimum value of 0.80. This result indicates that the proposed model achieves an acceptable balance between model fit. The Incremental Fit Index (IFI) is 0.935. The Comparative Fit Index (CFI) is also 0.935. Both values are above the recommended threshold of 0.90. These results provide strong evidence that the hypothesized relationships among the latent constructs adequately explain the covariance structure of the observed variables. The Root Mean Square Residual (RMR) was 0.076. It falls below the recommended maximum value of 0.08. This indicates that the average residual differences between the observed and reproduced covariance matrices are relatively small. The Root Mean Square Error of Approximation (RMSEA) is 0.067.The RMSEA value is below the widely accepted threshold of 0.08. It indicates an acceptable approximation of the model to the population covariance matrix.

Appendix

Construct	Code	Measurement Statement	Adapted from
Perceived Usefulness (PU)	PU1	Using generative AI based English language learning applications improves my English learning performance.	Davis (1989)
	PU2	These applications help me complete English learning tasks more effectively.	
	PU3	Using these applications increases my productivity in learning English.	
	PU4	Generative AI applications are useful for improving my English language skills.	
Perceived Ease of Use (PEOU)	PEOU1	Learning to use generative AI English learning applications is easy for me.	Davis (1989)
	PEOU2	Interacting with these applications is clear and understandable.	
	PEOU3	I find these applications easy to operate.	
	PEOU4	Becoming proficient in using these applications is easy for me.	
Attitude (ATT)	ATT1	Using GAI applications for English learning is a good idea.	Ajzen (1991)
	ATT2	I have a positive opinion about using these applications.	
	ATT3	I enjoy using generative AI for English language learning.	
	ATT4	I have a favorable attitude toward using these applications.	
Subjective Norm (SN)	SN1	People who are important to me think I should use GAI for English learning.	Ajzen (1991)
	SN2	My teachers encourage me to use these applications.	
	SN3	My classmates support the use of generative AI for English learning.	
	SN4	People whose opinions I value would approve of my using generative AI for English learning.	
Perceived Behavioral Control (PBC)	PBC1	I have the knowledge needed to use these applications effectively.	Ajzen (1991)
	PBC2	I have the necessary resources to use these applications.	
	PBC3	Using these applications is largely under my control.	
	PBC4	I am confident that I can use generative AI applications for English learning whenever I want	
Behavioral Intention (BI)	INT1	I intend to continue using generative AI applications for English learning.	Davis (1989); Ajzen (1991) Venkatesh et al. (2003)
	INT2	I will frequently use these applications in the future.	
	INT3	I will recommend these applications to other students.	
	INT4	I expect to use these applications whenever appropriate for learning English.	

Implications:-

The findings of this study have several important implications, for educators, higher education institutions and developers of generative AI-based English language learning apps. The strong influence of perceived usefulness suggests that students are more willing to adopt these applications, when they see how they improve their language learning. Moreover,the positive role of perceived ease of use shows that user friendly and accessible platforms can encourage wider acceptance. It is also to be noted that creating positive learning experiences with AI is just as important as providing the technology itself. Another point is that significant influence of subjective norm indicates that encouragement from teachers, and institutions can motivate students to use these applications more confidently. It is further recommended that students need adequate training, technical support, and access to digital resources to feel capable of using AI effectively.

Conclusion:-

The findings of this study demonstrate that the integrated Technology Acceptance Model and Theory of Planned Behavior provides a strong framework for explaining college students' intention to use generative AI based English language learning applications. All hypothesized relationships were supported. It confirms that perceived usefulness, perceived ease of use, subjective norm, perceived behavioral control, and attitude significantly influence students' behavioral intention to adopt these applications. Perceived usefulness emerged as the strongest predictor of attitude. Attitude was identified as the most influential determinant of behavioral intention. These findings highlight that both technological perceptions and social-psychological factors are crucial for promoting the acceptance of generative AI in English language learning. Future research may extend the present model by incorporating additional constructs such as trust, perceived risk, self-efficacy, facilitating conditions, AI literacy etc to further enhance its explanatory power.

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