The Role of Learning Motivation Factors in Deepseek Generative AI Adoption among Higher Education Students in India

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Abstract: This research explores adoption of the Deepseek, an artificial intelligence (AI) platform among higher education students in India by integrating the Technology Acceptance Model (TAM) with learning motivation factors. Given the rapid rise of AI-based platforms in educational sector, understanding their adoption is not only timely but also essential for ensuring equitable and effective learning outcomes. Addressing a critical research gap in understanding of rapidly evolving EdTech sector, the research blends constructs such as learning interest, achievement goals, self-efficacy, and subjective norms in expanding the typical TAM model. This integrative approach allows for a more holistic framework that captures both technological perceptions and learner-driven motivational factors, making the model especially relevant in emerging economies where educational technology adoption varies widely. Data were gathered using an online survey via Google Forms, providing 346 valid responses from students. The sample consisted of students from diverse academic disciplines, ensures representativeness across different fields of study and thereby enhancing the generalizability of the results. The data was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) through SmartPLS-3 software. The findings support the extended TAM model which indicated that learning interest and achievement goals have significant impact on perceived ease of use. Self-efficacy and subjective norms have significant impact on perceived usefulness and behavioral intention has significant impact on actual usage, demonstrating its pivotal role in technology adoption. These relationships suggest that motivation-related constructs are not peripheral but central in shaping how students interact with AI-powered platforms. This study advances the literature on educational technology by establishing a new TAM model as applied to AI-powered learning tools in emerging economies. The practical implications are that developers of Deepseek need to make the platform more user-centered in order to increase adoption. Future research avenues involve analyzing other contextual factors and longitudinal patterns of adoption over time. These findings provide useful insights for stakeholders who want to maximize AI learning tool integration in universities.

Keywords: Artificial Intelligence, DeepSeek, Higher education, Learning motivation, Learning interest, Education technology, PLS-SEM

1. Introduction

DeepSeek, a new artificial intelligence (AI) model, is transforming the process of seeking information by offering superior reasoning abilities, great computational efficiency, and ease of use (Kumar, 2025). In contrast to

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conventional search engines and generative AI models, DeepSeek combines several computational approaches, thus being especially useful in higher education environments, where students need precise, contextually appropriate, and well-organized answers (Jiang, Gao and Karniadakis, 2025). In contrast to popular models such as ChatGPT, DeepSeek has proven to outperform them in niche applications, such as mathematical computation, scientific computation, and code writing (Jahin et al., 2025). Its open-access status and flexibility render it a suitable instrument for augmenting online learning experiences at universities and colleges (Peng, Chen and Shih (2025).

DeepSeek has been applied to different industries with great success in healthcare (Egger et al., 2025; Faray de Paiva et al., 2025), accounting (Arabiat, 2025), and fintech (Krause, 2025). In the education field, DeepSeek has emerged as a disruptive innovation that can revolutionize digital learning. Its capacity to deliver customized tutoring, support scholarly research, and improve engagement with students has attracted educators and researchers (Allen, 2025). Chinese universities have significantly utilized DeepSeek in filling technological gaps within AI innovation to make students capable of creating sophisticated computational abilities (Allen, 2025). DeepSeek has also been promising in education testing, helping students solve difficult math problems with greater accuracy (Jahin et al., 2025).

Various research studies have compared the capabilities of DeepSeek and other AI models. Neha and Bhati (2025) compared DeepSeek models, where they emphasized the evolution of natural language processing and knowledge retrieval. Liao (2025) made a technical assessment of DeepSeek's large model, presenting its computational efficiency and real-time implementation across various fields. In addition, comparative analyses of DeepSeek and ChatGPT have highlighted its stronger mathematical reasoning and code generation abilities (Jiang, Gao and Karniadakis, (2025); Manik, 2025). Previous research has largely centered on the technical features of DeepSeek instead of the motivational and psychological aspects that shape its adoption (Kerimbayev et al., 2024). In addition, whereas research on educational generative AI has looked into usability, accessibility, and efficacy, there exists a gap in research to comprehend how motivation variables influence students' adoption of DeepSeek.

The main aim of this research was to analyze the behavioral intentions (BI) of Indian higher education students in adopting DeepSeek by combining the Technology Acceptance Model (TAM) with learning motivation variables. The research seeks to fill the current research gap by exploring how learning motivation variable affect students' intentions toward the ease of use and usefulness of DeepSeek. In addition, this study will examine the effect of these perceptions on BI and use behavior. Using a hypothesized research model (as shown in Figure 1), this study adds strength to the conventional TAM model by addressing important motivational factors. The interactions among these constructs will be empirically examined to shed light on the drivers of DeepSeek's adoption by students.

This research makes several contributions to the literature. First, it presents empirical findings on the determinants of DeepSeek adoption behavior among Indian students. Second, it extends the TAM model by adding learning motivation factors, providing a richer explanation of technology acceptance in learning environments. Third, the findings of this study will help educators, policymakers, and AI developers create more efficient AI-based learning tools that are responsive to students' learning requirements.

2. Literature Review

The Technology acceptance model (TAM) developed by Davis (1989) extends the Theory of Reasoned Action (TRA) to offer explanations of users' adoption of new technology (Fishbein & Ajzen, 1977). The original TAM developed by Davis (1989) identifies four constructs: perceived ease of use (PEU), perceived usefulness (PU), behavioral intention (BI), and actual use (AU). The TAM is very flexible in that it is possible to integrate external variables in order to extend its applicability. It has been widely applied and developed throughout the years through the integration of different external variables to study a range of settings.

In particular, TAM was successful in the prediction of students' motivation, behavior, and performance in using various technologies, such as evaluating college students' actual use of AI systems (Thummalapenta et al., 2025). It provides a solid theoretical basis for the comprehension of how users develop intentions to use and adopt new technologies based on PEU and usefulness. Various external variables have been incorporated into TAM since its creation to examine and study the acceptance and intention to use AI in higher education (Tummalapenta et al., 2024; Pasupuleti & Thiyyagura, 2024).

This research including factors of learning motivation as independent variables, such as learning interest (LI), achievement goals (AG), self-efficacy (SE) and subjective norms (SN). The above-mentioned factors are studied to check their influence on the acceptance and usage of DeepSeek by students in higher education. The expanded TAM model shown in Figure 1 seeks to present more sophisticated explanations of the roles played by students' desire to learn and motivation in creating perceptions, intention, and final adoption of DeepSeek.

Learning motivation is a crucial determinant of the education system, especially in the implementation of AI-based systems. It includes different sub-factors such as LI, AG, SN and SE (Riaz et al., 2010; Ngan & Law, 2015; Firdaus, 2019). Many studies have highlighted that these factors have a significant potential to affect students' behavioral intentions towards AI systems either positively or negatively (Bhavana & Vijayalakshmi, 2022; Liu et al., 2022; Wu, Liu and Huang (2022)). These are both predictive and motivational variables that impact students' adoption intention for AI tools such as DeepSeek (Dirzyte et al., 2021). Learning motivation is usually referred to as the process of decision-making that stimulates students to participate in certain learning activities and the amount of effort they put into them (Bandhu et al., 2024). Learning motivation can be explained as the sum of incentives that result in people choosing certain behaviors or goals (Jarvis, 2005).

This research takes into account four important dimensions of learning motivation: LI, AG, SE and SN. LI is a student's internal motivation and curiosity to learn content and work on tasks, which creates a stronger sense of attachment to the learning process (Harefa et al., 2023; Ariani, 2020). AG signifies the hope of reaching certain educational outcomes, usually inspired by the need to improve ability or prove expertise in a subject (Elliot & Thrash, 2001). SE is the belief by students in their capacity to effectively accomplish educational tasks with the aid of certain learning tools, affecting their motivation, persistence, and technology adoption (Compeau & Higgins, 1995). SN concern peer, educator, and general academic community pressures and expectations on students' adoption and use (Börger & Hattam, 2017).

Various studies have examined the effect of LI, AG, SE and SN on students' behavior regarding the use of AI systems, and consistently reported a strong effect on their adoption and usage behavior (Roy et al., 2022; Moon & Jung, 2016). All these factors have proven to be good predictors of students' intention to employ AI tools in education such as DeepSeek (Huang, 2020; Mudiarti & Harjanti, 2021; Shiang Tyng et al., 2023). Thus, in this research, hypotheses are developed that investigate the relationship of PU, PEU, and the various dimensions of learning motivation.

Students who are more interested in learning will find AI-based learning platforms such as DeepSeek easier to use. This is due to the fact that intrinsically motivated students are prone to exhibit exploratory behavior (Deci & Ryan, 2000), persevere in the face of initial usability issues, and achieve increased familiarity with features of a platform, ultimately making them feel more ease of use (Venkatesh et al., 2003). LI will have a positive impact on students' perceptions of DeepSeek's use. Based on self-determination theory (Deci & Ryan, 2000), intrinsically motivated learners are more likely to identify and value the degree to which the capabilities of the platform fit their curiosity-oriented learning objectives, and thus make more favorable use judgments. Hence we propose

***H1**: LI has significant positive impact on PEU*

***H2**: LI has significant positive impact on PU*

Students with more robust AG will find AI learning platforms more user-friendly. AG students proactively search for mastery strategies (Elliot & McGregor, 2001) and hence are more likely to systematically investigate platform features and overcome usability obstacles, thus reinforcing ease-of-use perceptions (Huet et al., 2011; Teo et al., 2024). AG learners will find DeepSeek's functions to be more useful. By the goal-setting theory (Locke & Latham, 2002), these students consciously assess instruments that facilitate the achievement of performance goals, rendering them more responsive to attributes that optimize learning effectiveness and quality (Miron-Spektor & Beenen, 2015). The connection could be especially robust for students with performance-approach goals. Hence, we hypothesize that,

***H3**: AG has significant positive impact on PEU*

***H4**: AG has significant positive impact on PU*

Higher SE students will find AI learning platforms more convenient to use. Social cognitive theory (Bandura, 1997) suggests that those with high confidence in their online skills are likely to exhibit exploratory behavior, overcome technical difficulties, and establish effective interaction strategies, resulting in increased ease-of-use perceptions (Compeau & Higgins, 1995). This might be less so for highly intuitive platforms where little skill is needed for simple usage. SE learners will find the functionalities in DeepSeek more useful. Those with high confidence in their ability to use technology (Seshadri & Pasupuleti, 2023; Rahmawati, 2019) are likely to learn complex features through consistent use, improvise platform tools to learning tasks creatively and identify performance gains - all factors that significantly influence usefulness assessments (Venkatesh & Davis, 2000). This should hold particularly true in situations where self-directed learning is required. Therefore we propose,

***H5**: SE has significant positive impact on PEU*

***H6**: SE has significant positive impact on PU*

Students who feel greater social pressure to employ AI learning platforms will indicate greater PEU. This is due to two mechanisms, one is informational social influence, whereby users gain from peer-shared information regarding platform navigation (Venkatesh & Davis, 2000), and second is normative conformity, whereby the need for social conformity lessens resistance to initial usability obstacles (Fishbein & Ajzen, 1977). SN will have a positive impact on PU of DeepSeek. When referent groups that are significant (peers, faculty) support use of the platform, students are likely to assign value to suggested features they may otherwise ignore (Tran, Nguyen and Tang, 2023), and reinterpret early experience with use through socially confirmed frameworks for interpretation (Binyamin, Rutter and Smith, 2018). This relationship is expected to strengthen when users have limited prior experience with similar technologies, making them more reliant on social cues for usefulness evaluation. Hence we hypothesize that,

***H7**: SN has significant positive impact on PEU*

***H8**: SN has significant positive impact on PU*

PEU is the level to which someone feels that making use of a particular AI system will not cause them much trouble and will only improve their performance (Davis et al., 1989). In education, this means it is the intention of students to accept or dismiss a technological use depending on whether they feel the use will do a good job of facilitating learning and academic progress (Tummalapenta et al., 2024). PU, however, refers to the degree to which a user feels that the use of a specific system will enhance their productivity without incurring undue physical or mental effort (Davis et al., 1989; Rosli & Saleh, 2023). Studies have uniformly shown that PEU and PU have a considerable influence on users' attitudes towards a specific technology, with both having a fundamental role in defining behavioral intention (Pasupuleti and Thiyyagura, 2025; Li et al., 2024).

Behavioral intention in TAM is the intentional choice to do or not do something with a technology in the future (Basaran & Aksoy, 2017). When applied to AI tools, it is the students' willingness to incorporate Deppseek into their studies and their resolve to do so repeatedly over a period of time (Kuleto et al., 2021). There is evidence in the existing literature that behavioral intention has a strong association with the usage of AI systems. Finally, AU is the dependent variable, symbolizing the use of the technology, which is highly driven by behavioral intention (Li, 2023). Guided by this explanation, the research establishes hypotheses regarding PEU, PU, and behavioral intention, as summarized below.

***H9**: PEU has significant positive impact on BI*

***H10**: PU has significant positive impact on BI*

***H11**: BI has significant positive impact on AU*

Figure.1 presents the theoretical model relating to the use of DeepSeek and identified motivational factors.

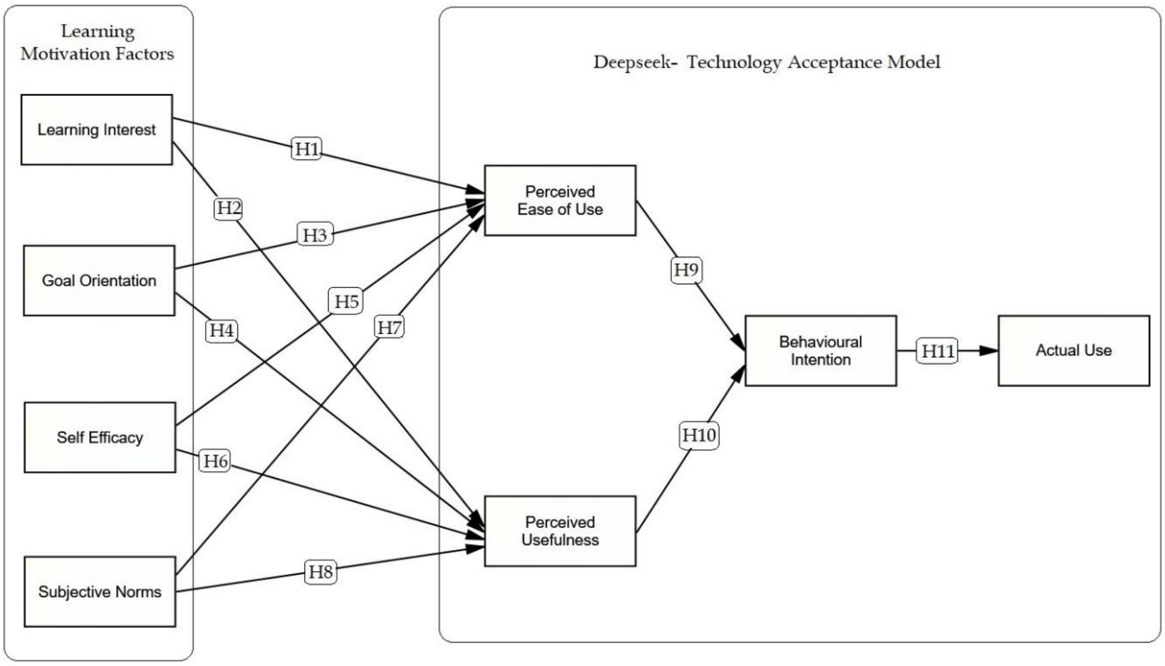

Figure.1: Proposed Research Model

3. Research Methodology

This research study used a quantitative research design to explore the determinants of DeepSeek use among Indian higher education students through the integration of the TAM and learning motivation factors. A systematic survey-based method was used for data collection, using an online Google Form that was disseminated through email and social networking sites. Participants were also asked to invite their friends and networks to take the survey, hence blending convenience sampling and partial snowball sampling.

The sample size was calculated using Partial Least Squares Structural Equation Modeling (PLS-SEM) recommendations. Since the research model has 8 variables and 31 measurement items, there should be at least 10 observations for every parameter estimate, resulting in a target sample size of 310 respondents. This agrees with guidelines from Hair et al. (2012) and Kline (2023), who state that SEM analysis must involve a minimum of 200 samples, and the bigger the sample the more elaborate the model. The questionnaire was kept brief and easy to use with inclusion of demographic items (gender, year of study, and course) and established scales from the literature. These constructs were assessed through a seven-point Likert scale (1 = strongly disagree and 7 = strongly agree). LI, AG, SE and SN measurement items were taken from Swarni (2024); Midgley et al. (1998); Chen, Gully and Eden (2001); and Van Acker et al. (2013), respectively. Four items each for PEU, PU and three items for AU were adopted from Davis (1989) and Tummalapenta et al. (2024), whereas BI was measured by scales developed by Park, Nam and Cha (2012). Prior to participation, participants were made aware of the study's aim, voluntary nature, confidentiality, and their right to withdraw at any time.

The study population was Indian higher education students who were aware about and using DeepSeek. Data collection occurred in February and March, 2025 and the survey was open until the second week day of March. Incomplete and inconsistent responses were excluded, and there remained 346 valid responses. Missing values and outliers were screened for in the dataset to maintain data quality. The final sample size was found to be adequate for further statistical analysis, such as measurement and structural equation modeling, to test the hypothesized relationships in the research model. By using a systematic data collection process and ensuring a representative sample, this research hopes to present meaningful findings into the factors driving DeepSeek adoption among Indian students.

4. Data Analysis and Results

The analysis used Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze the postulated relationships between learning motivation factors, TAM constructs, and concrete usage behavior. Results of measurement model validation and structural path analysis are presented and provide insights into the determinants of students' DeepSeek BI and use.

Before performing the measurement model analysis, we initially explored the demographic profiles of our survey respondents to understand about the composition sample. The analysis provided significant information regarding the participants' background and DeepSeek usage patterns. As shown in the table.1, gender distribution indicated slightly greater participation among male students (56.9%, n=197) than female students (43.1%, n=149). Academic program distribution indicated undergraduate students constituting the largest student group among respondents at 41.6% (n=144), followed by postgraduate students at 33.8% (n=117). Professional and specialized course students contributed 16.5% (n=57) of respondents, with doctoral and research scholars making up the lowest student category at 8.1% (n=28). This division corresponds with the conventional student structure of higher education systems. The year-by-year breakdown of participants showed greater participation by advanced students, with the third-year students being the biggest group (35.8%, n=124). Fourth-year students were second at 29.5% (n=102), with second-year and first-year students making up 19.7% (n=68) and 15.0% (n=52) respectively. This trend implies that students in more advanced years of study might be more interested in academic support resources such as Deepseek.

In terms of awareness of Deepseek, most of the respondents (53.5%, n=185) were both aware of and regularly using the platform. A considerable number (32.4%, n=112) reported awareness but sporadic use, while merely 14.2% (n=49) reported not being familiar with the tool. This reflects quite high awareness and uptake of Deepseek among the student population under study. Frequency of use information showed that the most frequent users comprised the majority (41.9%, n=145) who used it on a weekly basis, and then those using it daily (29.8%, n=103). There were 28.3% (n=98) rare users. The split indicates multiple levels of engagement with the platform, with a high percentage including it in their everyday study practices and others less regularly.

Table.1: Demographic Profile of the Survey Participants

Demographic Variable	Category	Frequency	Percentage
Gender	Male	197	56.9
	Female	149	43.1
Course Studying	Undergraduate (UG) Courses	144	41.6
	Postgraduate (PG) Courses	117	33.8
	Professional & Specialized Courses	57	16.5
	Doctoral & Research Programs	28	8.1
Year of Study	I Year	52	15.0
	II Year	68	19.7
	III Year	124	35.8
	IV Year	102	29.5
Familiarity with DeepSeek	No, I am not familiar with it	49	14.2
	Yes, but I am not using regularly	112	32.4
	Yes, I am familiar and using it	185	53.5
Frequency of Deepseek Usage	Daily	103	29.8
	Weekly	145	41.9
	Rarely	98	28.3

4.1 Measurement Model

The measurement model fit test calculated the reliability, convergent validity, and discriminant validity of the constructs through factor loadings and variance inflation factor (VIF) values. All factor loadings were more than the advised value of 0.70, reflecting very high item reliability (See Table.2). The values of VIF varied between 1.244 and 2.719, far below the conservative value of 5 as recommended by Hair et al. (2021), which ensures there are no problems of multicollinearity within the measurement model.

Table.2: Measurement Model: Item Loadings and Variance Inflation Factors

Construct	Items	Factor Loadings	VIF
Learning Interest	LI1: DeepSeek makes my academic tasks more interesting to me.	0.876	2.409
	LI2: I enjoy using DeepSeek for studying and completing assignments.	0.868	2.417
	LI3: DeepSeek increases my interest in learning new concepts.	0.795	1.884
	LI4: I am motivated to learn more because of the innovative features of DeepSeek.	0.881	2.359
Achievement Goals	AG1: Using DeepSeek helps me achieve my academic learning goals.	0.862	2.194
	AG2: DeepSeek assists me in meeting the academic requirements of my courses.	0.886	2.713
	AG3: I am more likely to reach my academic goals with the help of DeepSeek.	0.840	2.183
	AG4: I feel that using DeepSeek supports my progress toward academic success.	0.871	2.550
Self-Efficacy	SE1: I believe I have the ability to use DeepSeek for my academic tasks.	0.856	2.285
	SE2: I am confident that I am able to generate well-structured answers using DeepSeek	0.878	2.347
	SE3: I am confident that I am able to find relevant study materials using DeepSeek	0.827	1.984
	SE4: I am confident that I am able to use DeepSeek to improve my learning experience.	0.788	1.736
Subjective Norms	SN1: My peers encourage me to use DeepSeek for academic tasks.	0.857	2.245
	SN2: My instructors expect me to use DeepSeek in my coursework.	0.866	2.313
	SN3: My classmates believe that using DeepSeek is considered socially acceptable among students.	0.871	2.408
	SN4: My classmates generally expect me to use DeepSeek for learning and studying.	0.844	2.195
Perceived Ease of Use	PEU1: Learning how to use DeepSeek is easy for me.	0.839	2.028
	PEU2: My interaction with DeepSeek is clear and understandable.	0.857	2.156
	PEU3: I find DeepSeek easy to use.	0.857	2.218
	PEU4: It is easy for me to become skillful at using DeepSeek.	0.867	2.382
Perceived Usefulness	PU1: I find DeepSeek is useful in my daily life.	0.765	1.613
	PU2: Using DeepSeek helps me accomplish things more quickly.	0.797	1.726
	PU3: Using DeepSeek increases my productivity.	0.814	1.856
	PU4: Using DeepSeek helps me perform many things more conveniently.	0.717	1.244
Behavioral Intention	BI1: I intend to use DeepSeek regularly for my academic tasks in the future.	0.868	2.348
	BI2: I will strongly recommend others to use DeepSeek for learning and studying.	0.884	2.719
	BI3: I expect my use of DeepSeek for academic support to continue in the future.	0.868	2.343
	BI4: I intend to use DeepSeek for quick and easy access to information and learning resources	0.865	2.408

Construct	Items	Factor Loadings	VIF
Actual Use	AU1: I frequently use DeepSeek for academic tasks.	0.884	2.093
	AU2: My usage of DeepSeek for learning has increased over time.	0.860	1.899
	AU3: I rely on DeepSeek to complete major academic assignments.	0.879	2.182

The reliability and validity of the measurement model were tested by several criteria such as Cronbach's alpha, rho_A, composite reliability (CR), and average variance extracted (AVE). As shown in Table.3, all the constructs reflected good levels of internal consistency with Cronbach's alpha values ranging from 0.777 to 0.895, well above the threshold of 0.7. The rho_A values, being a more conservative measure of reliability, also closely replicated the alpha values, ranging from 0.777 to 0.895, again supporting the reliability of the scales.

Table.3: Construct Reliability and Convergent Validity

Variable	Alpha	rho_A	CR	AVE
LI	0.879	0.894	0.916	0.733
AG	0.888	0.893	0.922	0.748
SE	0.878	0.878	0.916	0.731
SN	0.777	0.777	0.856	0.599
PEU	0.858	0.862	0.904	0.702
PU	0.882	0.884	0.919	0.739
BI	0.895	0.895	0.927	0.760
AU	0.846	0.848	0.907	0.765

Composite reliability coefficients, which estimate the internal consistency of the latent constructs, were 0.856 to 0.927, all higher than the desired measure of 0.7. AVE scores, which estimate the variance explained by the construct in comparison to measurement error, were 0.599 to 0.765. Whereas the majority of constructs passed the 0.5 threshold, SN had a slightly lower AVE of 0.599, yet one that is still deemed acceptable within social science studies when composite reliability is satisfactory. The findings provide strong evidence of convergent validity since all the constructs achieved the reliability criterion and most of them surpassed the AVE criterion. LI had exceptionally good psychometric qualities with an alpha of 0.879, CR of 0.916, and AVE of 0.733. Likewise, BI had very high reliability with an alpha of 0.895, CR of 0.927, and AVE of 0.760. PEU and AU also demonstrated high reliability and validity, with CR values of 0.904 and 0.907 respectively.

The measurement model showed high discriminant validity using two corroborative assessment techniques: Fornell-Larcker criterion and the heterotrait-monotrait (HTMT) ratio. Both methods validated that all constructs in the model are empirically different and capture distinctive theoretical concepts. The Fornell-Larcker evaluation showed that square roots of AVEs (0.774 to 0.875) were larger than all corresponding inter-concept correlations in their respective columns and rows (See table.4). AG (AG) had particularly strong discriminant validity with a diagonal of 0.865 that over its highest correlation of 0.687 with AU (AU). Analogously, BI (BI) remained clear with a distinctiveness AVE root of 0.872 versus its strongest correlation of 0.566 with PEU (PEU).

Table.4: Discriminant Validity (Fornell-Larcker Criteria)

	AG	AU	BI	LI	PEU	PU	SE	SN
AG	**0.865**							
AU	0.687	**0.875**						
BI	0.529	0.482	**0.872**					
LI	0.468	0.502	0.485	**0.856**				
PEU	0.475	0.327	0.566	0.434	**0.838**			
PU	0.446	0.338	0.459	0.362	0.587	**0.859**		
SE	0.454	0.380	0.330	0.345	0.268	0.529	**0.855**	

	AG	AU	BI	LI	PEU	PU	SE	SN
SN	0.484	0.383	0.379	0.428	0.468	0.487	0.438	**0.774**

The HTMT analysis also supported these results, as all of the ratios were below the conservative mark of 0.85 (See table.5). These figures were safely below the discriminant validity threshold. SE was the least associated, as its highest HTMT ratio was 0.599 with PU, as expected, supporting its relative independence within the model. These results confirm the psychometric quality of the constructs and warrant their treatment as separate entities in further structural model analysis.

Table.5: Discriminant Validity (HTMT Ratio)

	AG	AU	BI	LI	PEU	PU	SE	SN
AG								
AU	0.792							
BI	0.593	0.551						
LI	0.521	0.579	0.549					
PEU	0.541	0.383	0.644	0.492				
PU	0.501	0.389	0.515	0.403	0.676			
SE	0.512	0.440	0.372	0.388	0.311	0.599		
SN	0.574	0.468	0.446	0.514	0.565	0.582	0.520	

4.2 Structural Model

After confirming reliability, convergent validity, and discriminant validity in the measurement model, we proceed to test the structural relationships between constructs (See Figure.2). The structural model analyzed the hypothesized paths between the proposed relationships. Using bootstrapping analysis (5,000 subsamples), we tested each relationship's significance and strength in order to assess their impact on students' adoption of DeepSeek. The results revealed that, nine out of the eleven hypothesized relationships were empirically supported, whereas two paths indicated non-significant effects (See Table.6).

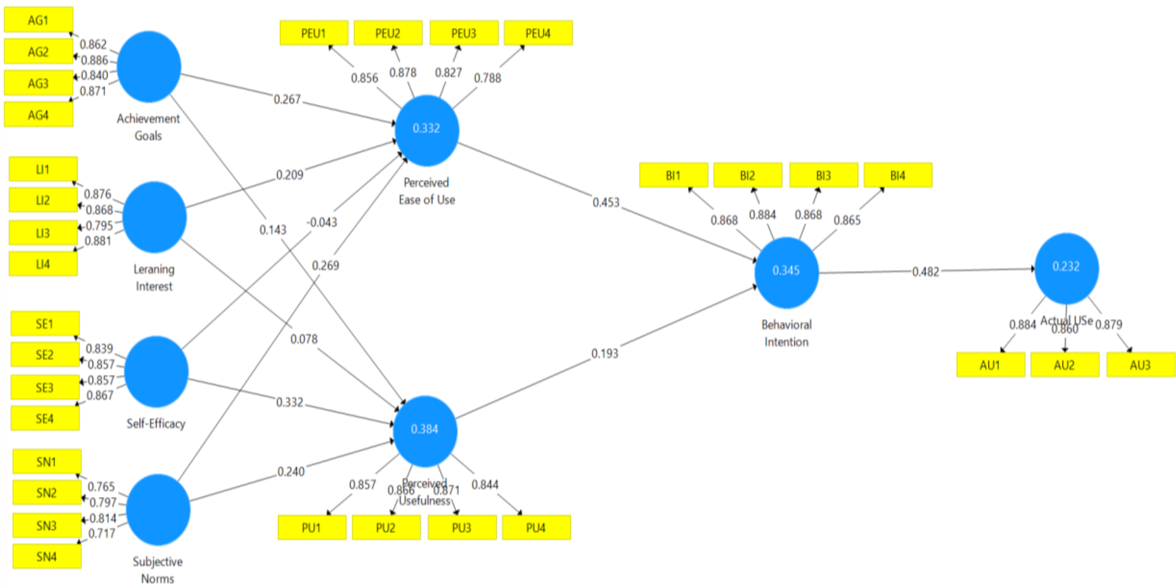

Figure.2: Structural Model

Table.6: Hypothesis Test Results

Hypothesis	Original Sample	Sample Mean	Std Dev	T Value	P Values	Result
LI → PEU	0.209	0.208	0.055	3.820	0.000	Significant
LI → PU	0.078	0.080	0.046	1.708	0.088	Not Significant

Hypothesis	Original Sample	Sample Mean	Std Dev	T Value	P Values	Result
AG → PEU	0.267	0.270	0.052	5.140	0.000	Significant
AG → PU	0.143	0.141	0.056	2.548	0.011	Significant
SE → PEU	-0.043	-0.044	0.055	0.785	0.433	Not Significant
SE → PU	0.332	0.332	0.052	6.401	0.000	Significant
SN → PEU	0.269	0.271	0.052	5.180	0.000	Significant
SN → PU	0.240	0.246	0.052	4.640	0.000	Significant
PEU → BI	0.453	0.453	0.052	8.657	0.000	Significant
PU → BI	0.193	0.193	0.055	3.535	0.000	Significant
BI → AU	0.482	0.483	0.052	9.290	0.000	Significant

LI had a strong positive impact on PEU ($\beta = 0.209$, $t = 3.820$, $p < 0.001$) but did not have a significant impact on PU ($\beta = 0.078$, $t = 1.708$, $p = 0.088$). AG revealed strong positive effects on both technology acceptance constructs, significantly predicting PEU ($\beta = 0.267$, $t = 5.140$, $p < 0.001$) and PU ($\beta = 0.143$, $t = 2.548$, $p < 0.01$). The analysis presented differing findings for SE. While it did not demonstrate a significant correlation with PEU ($\beta = -0.043$, $t = 0.785$, $p = 0.433$), it had a positive influence on PU ($\beta = 0.332$, $t = 6.401$, $p < 0.001$). SN proved to be a reliable predictor, having a significant impact on both PEU ($\beta = 0.269$, $t = 5.180$, $p < 0.001$) and PU ($\beta = 0.240$, $t = 4.640$, $p < 0.001$). The TAM relationships were fully supported. PEU had a strong influence upon BI ($\beta = 0.453$, $t = 8.657$, $p < 0.001$), as did PU ($\beta = 0.193$, $t = 3.535$, $p < 0.001$). The terminal path from BI to AU was especially significant ($\beta = 0.482$, $t = 9.290$, $p < 0.001$), accounting for a large level of usage variance. These findings are largely in line with the integrated theory framework, where LI, AG, and SN play significant roles as antecedents to technology acceptance constructs. The final strong path from BI to AU confirms the model's predictive validity in explaining DeepSeek adoption among Indian higher education students.

5. Discussion

The strong positive relationship between LI and PEU supports that intrinsically motivated learners perceive DeepSeek to be easier to use. This finding aligns with Venkatesh and Bala's (2008) extension of the TAM, which demonstrated that learning-focused individuals are more likely to develop adequate mental representations of new systems, thereby enhancing their PEU. In the present context, the results suggested that curiosity-oriented activity assists students in overcoming initial technology challenges through exploratory behavior. This interpretation is consistent with earlier studies in educational technology, such as Wu, Liu and Huang (2022), which emphasized the role of intrinsic interest in facilitating smoother adoption of digital tools. However, LI did not have a significant impact on PU. This outcome stands in contrast to some earlier research in educational technology, at the same time this result is consistent with Zhai and Shi (2020), who found that LI alone is insufficient to ensure PU unless its immediate connection with academic performance is established . This non-significant association suggests that while students find the platform enjoyable, they do not independently recognize its usefulness unless it explicitly demonstrates academic values. .

The robust positive influences of AG on both PEU and PU validate the well-established association between AG and technology judgment. These findings are consistent with Elliot and Thrash (2001) whose AG theory emphasized that goal-directed learners systematically evaluate functional characteristics of the tools. In this study the more significant influence on PEU specifically substantiates Teo et al. 2024, who argued that achievement-oriented users place greater value on interface efficiency when selecting learning tools. This suggested that for learners with strong AG, PEU becomes a decisive factor in adopting educational technologies.

In contrast, the non-significant relationship between SE and PEU is in conflict with standard TAM extensions but receives support from prior literature. This aligns with Wang and Tseng (2010), who reported that SE predicts PEU less accurately when intelligent systems are equipped with adaptive interfaces designed to accommodate varying skill levels. Yet, the strong SE to PU relationship reaffirms Bandura's (1997) social cognitive theory and also consistent with Rahmawati (2019) in e-learning context, where efficacy beliefs were shown to significantly impact use decisions. Thus, while SE may not directly determine perceptions of ease of use, it remains a critical driver of PU of AI- enabled learning systems.

The results also indicated that, SN significantly predicted technology acceptance variables, confirming Venkatesh and Davis' (2000) normative influence hypotheses. The stronger influence of SN on PEU compared to PU builds on findings from Bhimavarapu et al. (2024) and Banala et al. (2024). Specifically, these results suggested that word-of-mouth recommendations and peer influence may initially reduce perceived complexity before building use beliefs in educational AI scenarios. These results reiterate the dual social influence mechanism in technology adoption proposed by Morris and Venkatesh (2010). Furthermore, the relationships between PEU, PU and BI reaffirm Davis' (1989) original TAM hypotheses in the context of AI-based learning environments. Notable, the increased PEU effect confirms emerging evidence by Scherer, Siddiq and Tondeur (2019) in educational app adoption, which emphasizes that usability continues to be the key driver of adoption, particularly in voluntary usage environments. Lastly, the positive relationship between BI and AU is in consistent with Pasupuleti and Seshadri (2023) as well as Ajzen's (1991) theory of planned behavior under barrier-free conditions. In the context of AI in education this finding aligns with Wu, Liu and Huang (2022) further demonstrating that BI strongly translates into AU when contextual constraints are minimized.

6. Implications, Limitations, Future Research Directions and Conclusion

The findings of the study have significant implications across theoretical, practical, and methodological areas. From a theoretical point of view, the findings extend our knowledge on technology acceptance in learning contexts by illustrating how various motivational factors work through different routes. The results indicate that theories of educational technology adoption must explain these differential motivational processes. These results build on conventional technology acceptance models by integrating educational psychology perspectives, specifically how intrinsic and achievement-based motivations affect technology perceptions and use differently. The practical applications for teachers are significant and multi-faceted. Teachers need to prioritize initial training and support in order to help students overcome early usability hurdles. Establishing opportunities for peer sharing and modeling of good use can have a strong impact on adoption. Teachers can create guided activities in which students show and think about their application of the technology, thus reinforcing competence beliefs and social norms of proper use.

For designers and implementers of educational technology, the findings point to a number of design and implementation considerations. The priority of ease-of-use perceptions implies that interface design should reduce initial learning curves while offering transparent paths to uncover more sophisticated features. The high intention-behavior relationship implies that systems that make first-time use easy and rewarding will likely experience high rates of adoption. Developers could integrate smart onboarding mechanisms that respond to users' levels of demonstrated competence, with focused support building confidence through increasingly advanced functionalities. The social influence results imply that features facilitating peer sharing and exposure to others' usage patterns can strongly increase adoption.

At an institutional level, the research highlights the need for robust support structures for the integration of educational technology. The different motivational pathways that have been identified imply that homogeneous training schemes might prove less effective than differentiated programs targeting different user dispositions. Institutions may, therefore, want to establish multiple onboarding paths, e.g., different resources for students whose primary motivation is interest versus those whose goal is achievement outcomes. Strong social influence effects show that building communities of practice on educational technologies in which both teachers and students share experiences and best practices could potentially lead to improved adoption and usage.

These collective implications imply that successful educational technology integration demands consideration of several interrelated factors - individual motivation, social contexts, institutional supports, and technology design characteristics. The findings extend beyond simplistic "if you build it they will come" assumptions about educational technology, instead portraying a more realistic picture of the psychological and social processes involved in successful adoption. This insight can be used to develop more advanced technology implementation strategies for educational environments that can result in increased adoption and better utilization of these powerful learning tools.

6.1 Limitations and Future Research Directions

A number of avenues for future research open up on the basis of the present study's results. First, cross-cultural comparison studies would establish whether these results generalize across varied educational systems and national cultures, especially in the face of the observed social influence effects. Second, experimental research would be able to test interventions specifically aimed at reinforcing specific motivational routes, e.g., interest-evoking features versus achievement-focused functionalities. Third, the influence of individual differences outside those considered in this research, including learning styles or personality, should be explored to create more inclusive models of educational technology adoption. Fifth, qualitative methods might shed more light on the cognitive processes behind the found relationships, especially concerning how students subjectively assess ease of use versus usefulness in actual learning contexts. Sixth, studies focusing on how these psychological variables interact with varying technological designs might advise more sophisticated educational technology design. Finally, longitudinal studies can monitor how the found relationships change as users move from initial adoption to long-term use. Such research may indicate whether ease-of-use perceptions lose significance as users accumulate experience, whereas usefulness perceptions become more important.

6.2 Conclusion

This research offers useful insights into the factors that drive DeepSeek adoption by Indian higher education students using an integrated theoretical model that integrates TAM and learning motivation factors. The results confirm that various motivational factors work through different paths, with AG and SN having particularly robust effects on adoption-related perceptions. The strong intention-behavior relationship indicates that well-designed instructional technologies can indeed successfully translate favorable attitudes into real use when implementation obstacles are kept to a minimum. The findings emphasize the significance of taking both individual psychological aspects and social influences into account in the implementation of instructional technologies. Although the research was conducted specifically on DeepSeek within the Indian context of higher education, the theoretical findings and methodological strategies could potentially generalize to applying educational technology to multiple platforms and cultures. The results as a whole add to richer models of technology acceptance in educational settings and offer practical advice to educators, developers, and policymakers seeking to further the effective incorporation of learning technologies. Subsequent research based on these findings can further develop our knowledge of the intricate interrelationship between human factors and technological characteristics in learning environments.

AI Statement: The authors declare that AI tools were not used in this study for the paper's conception, revision, or the creation of figures and tables.

Ethics Statement: All participants provided informed consent by proceeding after reading a statement on the study's purpose, anonymity, and voluntary nature of participation.

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