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RESEARCH ARTICLE

Exploring DeepSeek Adoption in Higher Education in Bangladesh: A UTAUT-Based Approach

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Abstract The integration of large language models (LLMs) into higher education is rapidly transforming learning and research processes. This study investigates the adoption of one such tool, DeepSeek, a Chinese LLM, in Bangladesh's higher education sector. It introduces geopolitical concern as a novel construct within the extended unified theory of acceptance and use of technology (UTAUT) framework to assess how national security, strategic alignment, and technological dependency influence trust, privacy concerns, and the behavioural intention to adopt AI tools in an academic context. A quantitative survey of 202 Bangladeshi university students was conducted using the extended UTAUT model. Partial least squares structural equation modelling was employed to analyse the impact of constructs such as performance expectancy, effort expectancy, and geopolitical concerns on behavioural intention and use behaviour. Geopolitical concerns significantly shaped trust and privacy perceptions, indirectly reducing adoption intentions. Despite privacy risks, students viewed DeepSeek in a favourable light due to its free access, cultural alignment, and potential to reduce Western tech dependency. Performance expectancy and facilitating conditions were key drivers of adoption, while social influence and hedonic motivation had negligible effects. This study contributes to the integration of geopolitical factors into AI adoption frameworks, highlighting Bangladesh's unique position amid a growing diversity of globally available AI models. It emphasises the need for culturally congruent, sovereignty-sensitive AI tools in the Global South. Policymakers and AI developers should address geopolitical sentiments and infrastructure gaps (e.g., internet reliability) to foster adoption. DeepSeek's frugal innovation model provides a blueprint for emerging economies seeking affordable AI solutions.

Keywords generative AI, artificial intelligence, DeepSeek, UTAUT, PLS-SEM

1 Introduction

The release of DeepSeek represents a major advancement in the global development of AI, thereby providing a powerful new option, marking what many authors call the "Sputnik moment" in AI. DeepSeek stands out due to its mixture of experts architecture, open-source availability, and high performance in reasoning tasks, thereby positioning China as a serious contender in the global AI landscape (Fernandes et al., 2025; Ramalho et al., 2024; Rocha, 2023). While US-based models, such as ChatGPT, dominate commercial applications, their accessibility remains limited in low-income regions in the world. For example, in countries such as India, Pakistan, and Bangladesh, a 25 USD monthly ChatGPT subscription can exceed 10% of the average monthly income, thus placing it well beyond the reach of ordinary users. In contrast, DeepSeek offers a compelling value proposition: it is freely available, supports local deployment, and can be adapted to national values and languages—key factors for digital sovereignty in the Global South (Batista et al., 2024; DeepSeek-AI et al., 2024; DeepSeek-AI et al., 2025).

In the context of the AI race, the Indian subcontinent emerges as a key region due to its vast and largely untapped market of over 1.7 billion consumers. Although it may look relatively small on the map

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next to India, China, and Pakistan, Bangladesh is the eighth-most populous nation in the world—with a population of over 175 million people—surpassing that of Russia. With an average economic growth of over 6% in the last 20 years, Bangladesh has gained a reputation as Asia's next tiger economy (International Monetary Fund, 2020). Bangladesh maintains a balanced and pragmatic position (Huang et al., 2023; Silver et al., 2023). However, following the significant political changes in July 2024, the country is at a crossroads and its technological policy decisions have become highly influential in the global AI landscape.

This study aims to explore the adoption of DeepSeek in Bangladesh. To achieve this, the extended unified theory of acceptance and use of technology (UTAUT) framework was further extended by integrating new constructs such as trust, perceived risk, and a novel variable—geopolitical concern. By focusing on how generative AI (GenAI) technologies can improve higher education in South Asian countries such as Bangladesh, this article contributes to advancing the educational goals outlined in Sustainable Development Goal 4—Quality Education (Hossain et al., 2025a; Hossain et al., 2025b; Hossain et al., 2026).

2 Literature Review

Several studies have sought to explore the adoption of GenAI tools across various sectors such as tourism, medicine, and education (Borges et al., 2024; Paiva, 2022; Pinto et al., 2022b). The authors performed a meta-analytic structural equation modelling to analyse findings from 61 articles, thereby encompassing a total sample of 21,499 participants across 30 countries that focus on adopting GenAI in higher education (Pinto et al., 2025a; Pinto et al., 2025b; Pinto et al., 2025c). The goal was to explore the relationships among key variables in the technology acceptance model (TAM), focusing on the adoption of GenAI tools. The results revealed that a large number of studies came from the Indian subcontinent: India (5 studies), Pakistan (2 studies), Nepal (2 studies), and Sri Lanka (1 study). Overall, the study supports the TAM hypothesis, which demonstrates the significant impact of perceived ease of use and usefulness on GenAI adoption.

Further, the technology continuance theory was extended via a quantitative partial least squares (PLS)-structural equation modelling (SEM) study that involved 310 Indian university students with external variables (perceived anthropomorphism, perceived intelligence, and technology novelty) to explore the factors influencing the continuance intention to use GenAI tools in higher education (Singh & Paiva, 2025). Using SmartPLS 4.0, the study found that perceived intelligence was the strongest predictor of perceived ease of use and usefulness, while anthropomorphism had a weaker impact. Moreover, attitudes and satisfaction were the strongest predictors of the continuance intention to use GenAI tools.

According to a qualitative study based on 14 semi-structured interviews with university professors (Paiva, 2024), the adoption of GenAI tools in the Indian subcontinent is being hampered by several issues. These difficulties include poor internet connectivity and infrastructure, AI bias and its inability to adjust to Indian cultural norms, lack of support for Indic languages, and the high cost of using such technologies. These regional restrictions highlight the need to thoroughly comprehend how DeepSeek and other AI tools are viewed and utilised in various cultural and infrastructure contexts.

Since most studies concentrate on American LLMs, such as ChatGPT or Microsoft Copilot, there is a clear gap in the literature on the adoption of Chinese LLMs such as DeepSeek (Pinto et al., 2025a). Hence, this study seeks to fill the gap in the literature by examining DeepSeek's adoption and usage patterns across the South Asian nation of Bangladesh.

3 Conceptual Framework

3.1 | UTAUT

Venkatesh et al. (2003) initially developed the UTAUT framework to explore the adoption of information systems by consolidating the contributions of eight models. The first UTAUT model only had four variables—performance expectancy (PE), effort expectancy (EE), social influences (SI), and facilitating conditions (FC) (Pinto et al., 2022a). PE refers to the belief that using DeepSeek will enhance task performance, such as improving data search and analysis effectiveness. EE is the perceived ease of use of DeepSeek, with a focus on its user-friendly interface. Behavioural intention (BI) refers to the strength of a student's willingness and plan to use DeepSeek for their academic activities (Hoehle et al., 2012). Use behaviour captures the actual utilisation of DeepSeek for specific academic tasks, such as research, assignment completion, and exam preparation. SI captures the impact of peers, colleagues, or trusted figures, such as educators and industry leaders, on an individual's decision to adopt DeepSeek, thereby reflecting the role of recommendations in shaping adoption behaviour. FC refers to the availability of resources, support, and infrastructure, such as internet connectivity, technical support, and training programs, which enable users to use DeepSeek effectively. The following hypotheses outline the relationships among these constructs:

- **H1: PE → BI**. PE positively influences BI to

use DeepSeek (Arachchi & Samarasinghe, 2024; Ivanov et al., 2024; Li, 2025; Liu et al., 2024; Sharma et al., 2024).

• **H2: EE → PE**. EE affects PE to use DeepSeek (Arachchi & Samarasinghe, 2024; Ivanov et al., 2024; Li, 2025; Liu et al., 2024; Sharma et al., 2024).

• **H3: SI → BI**. SI impacts BI to use DeepSeek (Biloš & Budimir, 2024; Liu et al., 2024).

• **H4: FC → BI**. FC positively influences BI to use DeepSeek (Biloš & Budimir, 2024; Li, 2025).

In 2012, the original UTAUT model was extended to UTAUT2 by adding three additional constructs to overcome the limitations of the original model: hedonic motivation (HM), price value (PV), and habits (HB) (Venkatesh et al., 2012). HM refers to the pleasure or enjoyment derived from using a technology, which can drive individuals to continue using a platform such as DeepSeek, particularly when the experience is enjoyable or rewarding. PV typically refers to the trade-off between cost and benefits; in the case of DeepSeek, since the platform is free, this construct can be interpreted in terms of users perceiving the platform as providing significant value for no monetary cost, such as time saved or efficiency gained in using it. HB represents the extent to which using DeepSeek becomes automatic or routine over time; the more frequently a user interacts with the platform, the more ingrained it becomes in their daily workflow, thus leading to its continued use. Thus, the following hypotheses are tested:

• **H5: HM → BI**. HM drives BI to use DeepSeek (Biloš & Budimir, 2024).

• **H6: PV → BI**. PV positively affects BI to use DeepSeek (Biloš & Budimir, 2024).

• **H7: HB → BI**. HB positively affects BI to use DeepSeek (Biloš & Budimir, 2024).

From the perspectives of the UTAUT and UTAUT2 models, both trust (TR) and privacy concerns (PC) play a significant role in shaping users' BI to adopt DeepSeek. To clarify the key constructs in the context of this study, we define them in the following manner. TR is defined as the belief that DeepSeek is reliable, provides accurate information, and handles user data in an ethical manner. In this context, privacy concern encompasses users' apprehension regarding how their personal and academic data is collected, utilised, and stored. A key factor that influences this concern in Bangladesh is data localisation—specifically, that user data is not stored in the country. This creates fears that data could be misused by the service provider without familiar due process and sufficient user transparency. These concerns are amplified by technical reports; for example, an analysis from Center for Strategic and International Studies highlighted potential risks associated with DeepSeek's open-source design, which could lower the barrier for creating malicious code (Pearl et al., 2025). Thus, the following hypotheses are tested:

• **H8a: TR → PC**. TR influences PC (Balaskas et al., 2025).

• **H8b: TR → BI**. TR positively affects BI to use DeepSeek (Balaskas et al., 2025; Hoehle et al., 2012; van der Heijden et al., 2003).

• **H8c: TR → EE**. TR improves perceptions of EE (Balaskas et al., 2025).

• **H9: PC → BI**. PC positively affects BI to use DeepSeek (Biloš & Budimir, 2024; Liu et al., 2024).

3.2 | A New Construct: Geopolitical Concerns

In the context of rising geopolitical tensions and digital sovereignty debates, this study introduces and develops a novel construct—geopolitical concerns (GC). This new construct seeks to measure how users' decisions to adopt new technologies are influenced by their attitudes towards the country of origin. This construct can be broken down into three subdimensions: perceptions of national security risks, strategic alignment, and technological dependency.

In addition, it is important to note that the GC construct is fundamentally distinct from xenophobic or ethnically motivated prejudice, but seeks to measure legitimate concerns regarding the actions of a state on the world stage. For example, users may reject DeepSeek not due to racial prejudice towards the Chinese people but due to concerns that the platform's governance and data policies may not align with local digital sovereignty preferences or familiar legal frameworks. Thus, the following hypotheses are tested:

• **H10a: GC → TR**. GC influences perceptions of TR.

• **H10b: GC → PC**. GC influences PC.

Finally, the authors acknowledge that there is a possibility that consumers boycott Apps from certain countries in response to geopolitical events. A particularly relevant example would be India's decision to ban TikTok and other Chinese Apps amidst heightened tensions between India and China over border clashes (Kumar & Thussu, 2023; Santos, 2023). While governments might take the initial first step of banning certain Apps, the ensuing public outcry and rising nationalist sentiment can lead consumers to not only adhere to these bans but also go beyond government actions by proactively avoiding using products or services from certain countries.

4 Research Method

4.1 | Proposed Research Model

This study systematically analyses the relationship

between the UTAUT and UTAUT2 variables and the intention to use DeepSeek. Consequently, the authors proposed a structural equation research framework, illustrated in Figure 1.

4.2 | Measurement Variable and Data Collection

An online questionnaire was administered in April 2025 to collect data from Bangladeshi university students. The confidentiality and anonymity of participants were assured and participation was voluntary. All questionnaire items were measured using a 5-point Likert scale (Pinto et al., 2022a). A pilot test was conducted with 20 questions, and final adjustments were made. In the data analysis phase, using SmartPLS 4.0, the authors conducted path analysis using PLS-SEM. The consistent PLS algorithm was selected because most constructs were modelled as reflective and not all variables follow a normal distribution.

Since PLS-SEM analysis requires a random and independent sample of at least 200 participants, the sample sizes are sufficient to meet this criterion (Boomsma & Hoogland, 2001). The questionnaire was completed by 202 participants from Bangladesh, consisting of 107 females (53%) and 95 males (47%).

5 Main Results

5.1 | Reliability and Validity Analysis

Partial least squares regression, a form of SEM in SmartPLS, was performed to confirm the validity and reliability of the model and constructs (Falk & Miller, 1992; Hair & Sarstedt, 2019). First, it is important to estimate the individual reliability of each item. Electronic Supplementary Material contains a table with the questions utilised, the sources of the items, individual outer loadings (λ), the mean, and the standard deviation. For applied research, each item must have an outer loading λ of at least 0.7 (Hussain et al., 2018; Nunnally, 1978).

Second, the reliability and validity of the survey were assessed using composite reliability (CR) derived from exploratory factor analysis. In Table 1, all the key constructs have a CR of above 0.7. The average variance extracted (AVE) was calculated to examine the convergent and divergent validity. Convergent validity is assured because all constructs have an AVE of above 0.5 (Fornell & Larcker, 1981). Divergent validity is also assured because the positive square root of the AVE for all factors is higher than the highest correlation with any other factor.

5.2 | Model Fit and Quality Indicators

Table 2 presents the model fit indicators for both the saturated and estimated models to evaluate the model's fitness to the observed data. The standardised root mean square residual (SRMR) measures the average magnitude of residuals, where values below 0.08 typically indicate a good fit (Hu & Bentler, 1998). The saturated model meets this criterion (SRMR = 0.061). However, the estimated model, which tests the specified structural relationships, exceeds this threshold (SRMR = 0.177), thereby suggesting that the hypothesised paths do not fully capture the complexity of the data covariance structure. The d_{ULS} (squared Euclidean distance) and d_G (geodesic distance) indices assess the discrepancy between the observed and model-implied

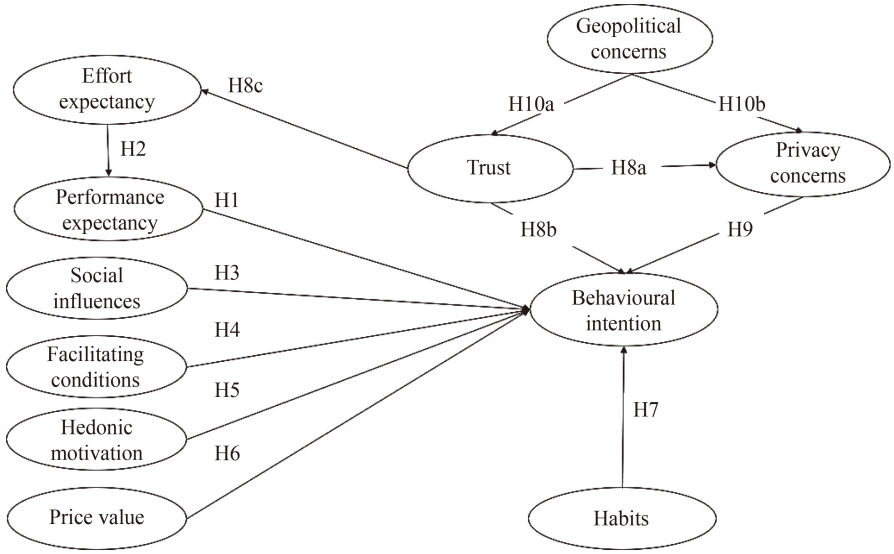

Figure 1 Research model on the relationship between the UTAUT and UTAUT2 variables and the intention to use DeepSeek.

Table 1 Composite reliability, average variance extracted, and correlations

	CR	AVE	BI	EE	FC	GC	HM	HB	PC	PE	PV	SI	TR
BI	0.94	0.70	0.84										
EE	0.91	0.83	0.60	0.91									
FC	0.90	0.81	0.63	0.57	0.90								
GC	0.93	0.67	0.66	0.48	0.59	0.82							
HM	0.93	0.82	0.65	0.49	0.48	0.54	0.90						
HB	0.89	0.74	0.64	0.43	0.49	0.59	0.58	0.86					
PC	0.94	0.80	0.48	0.32	0.32	0.52	0.56	0.37	0.89				
PE	0.90	0.69	0.75	0.60	0.57	0.65	0.64	0.58	0.46	0.83			
PV	0.92	0.78	0.75	0.63	0.62	0.65	0.69	0.63	0.45	0.72	0.89		
SI	0.89	0.80	0.57	0.56	0.59	0.53	0.47	0.42	0.32	0.60	0.61	0.89	
TR	0.92	0.75	0.64	0.50	0.50	0.57	0.52	0.60	0.38	0.54	0.65	0.49	0.87

Notes. The diagonal elements showing the square root of AVE for each construct. CR: composite reliability, AVE: average variance extracted, BI: behavioural intention, EE: effort expectancy, FC: facilitating conditions, GC: geopolitical concerns, HM: hedonic motivation, HB: habits, PC: privacy concerns, PE: performance expectancy, PV: price value, SI: social influences, TR: trust.

Table 2 Model fit indicators

Model type	SRMR	d_{ULS}	d_G	chi-square	NFI
Saturated model	0.061	2.884	1.523	1861.323	0.727
Estimated model	0.177	24.449	2.028	2146.705	0.685

Notes. SRMR: standardized root mean square residual, d_{ULS}: squared Euclidean distance, d_G: geodesic distance, NFI: normal fit index.

covariance matrices, with lower values indicating a better model fit. This discrepancy is not interpreted as a model failure but rather as an expected outcome given the study's context and objectives. Specifically, the introduction of the novel geopolitical concern construct—a multifaceted variable capturing perceptions of national security, strategic alignment, and technological dependency—introduces inherent complexity that a purely confirmatory model cannot fully capture.

The chi-square tests the null hypothesis that the model perfectly fits the data, with high values indicating potential discrepancies between the model and the observed data (Lohmöller, 1989). Both models show significant chi-square values (1861.323 and 2146.705, respectively), which is not uncommon in complex models with large sample sizes. The normal fit index (NFI) compares the chi-square value of the model to a null model. Given that values close to 1 indicate a better fit, both models show an acceptable fit (0.727 and 0.685, respectively). While they are below the ideal threshold of 0.90, these values are considered acceptable in exploratory research, particularly when introducing novel theoretical constructs (Hair & Sarstedt, 2019).

5.3 | Results of the Hypotheses Tests

Utilising the consistent PLS-SEM algorithm technique, the path coefficients (β) and Cohen's F statistic (F^2) were obtained for each hypothesis, as presented in Table 3 (Vinzi et al., 2010).

In the subsequent stage of analysis, the explanatory capability of the model was assessed through the coefficient of determination (R^2), which measures the amount of variance accounted for in each construct (Falk & Miller, 1992; Stone, 1974). R^2 ranges from 0 to 1, with higher values indicating greater explanatory power. As a general rule, R^2 values of 0.25, 0.50, and 0.75 can be regarded as weak, moderate, and considerable, respectively. The model explains a substantial proportion of the variance in BI (R^2 = 0.710). For the other constructs, the explained variance is moderate for PE (R^2 = 0.356) and TR (R^2 = 0.325), and smaller for PC (R^2 = 0.283) and EE (R^2 = 0.253).

Figure 2 presents a summary of the research model.

5.4 | Discussion

The results revealed that the main factor that influenced BI was PE, thereby confirming H1. The findings corroborate previous studies that demonstrated how GenAI tools can improve academic performance by reducing the amount of time needed to complete assignments and providing prompt answers to questions (Ivanov et al., 2024; Li, 2025; Liu et al., 2024; Sharma et al., 2024).

Furthermore, just like in previous studies, EE predicts PE, thereby confirming H2 (Arachchi & Samarasinghe, 2024; Ivanov et al., 2024; Li, 2025; Liu et al., 2024; Sharma et al., 2024). Students from Bangladesh are more likely to embrace and use DeepSeek if they believe it to be user-friendly,

Table 3 Path coefficient analysis

Hypothesis	Path	Path coefficient	F^2	p-value	Support
H1	PE → BI	0.294	0.116	0.000***	Not rejected
H2	EE → PE	0.597	0.553	0.000***	Not rejected
H3	SI → BI	0.009	0.000	0.893	Rejected
H4	FC → BI	0.157	0.044	0.009**	Not rejected
H5	HM → BI	0.062	0.005	0.241	Rejected
H6	PV → BI	0.195	0.040	0.014*	Not rejected
H7	HB → BI	0.125	0.027	0.102	Rejected
H8a	TR → PC	0.115	0.012	0.183	Rejected
H8b	TR → BI	0.132	0.030	0.011*	Not rejected
H8c	TR → EE	0.503	0.339	0.000***	Not rejected
H9	PC → BI	0.075	0.013	0.097	Rejected
H10a	GC → TR	0.570	0.482	0.000***	Not rejected
H10b	GC → PC	0.458	0.197	0.000***	Not rejected

Notes. Significance levels: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. Effect size interpretation for F^2: 0.02 (small), 0.15 (medium), 0.35 (large). BI: behavioural intention, EE: effort expectancy, FC: facilitating conditions, GC: geopolitical concerns, HM: hedonic motivation, HB: habits, PC: privacy concerns, PE: performance expectancy, PV: price value, SI: social influences, TR: trust.

particularly if they appreciate its multilingual features (which include support for Bengali and other regional languages such as Rangpuri, Sylheti, Chittagonian, and Noakhailla) and its real-time response refinement.

Contrary to expectation, SI did not play a significant role in shaping the BI to use AI chatbots such as DeepSeek in our study. In Bangladesh, students have largely taken the initiative of adopting GenAI out of their own volition rather than by being influenced by their peers, family members, or professors. This indicates a growing sense of digital individualism among Bangladesh's youth and may signal evolving patterns in how technology adoption unfolds in collectivist societies. These findings challenge conventional assumptions about collectivist societies, suggesting that digital technologies may be fostering a form of "networked individualism" where students make autonomous adoption decisions independent of traditional social structures.

FC significantly predict the BI to use AI chatbots such as DeepSeek, thereby confirming H4. Based on the answers provided by students in the questionnaire, it is evident that while students often have the know-how and technical support to utilise platforms such as DeepSeek, they often lack the necessary resources due to poor internet connectivity. According to Ookla's (2025) Speedtest Global Index, Bangladesh ranks 88th out of 111 in the world for mobile internet speeds. Frequent power outages, brownouts, and internet blackouts, such as those seen during the July Revolution, disrupt the consistent utilisation of such technologies.

Unlike what was initially hypothesised, HM did not play a significant role in shaping the BI to utilise AI chatbots such as DeepSeek; thus, H5 was rejected with 95% confidence (Biloš & Budimir, 2024). Bangladesh, like many collectivist cultures, emphasizes utility over enjoyment in technology adoption. This pragmatic orientation is intensified by the country's competitive job market, where a controversial quota system reserves government positions for specific groups. For students who do not qualify for these quotas—particularly those from non-quota backgrounds—academic success becomes the primary pathway to secure employment.

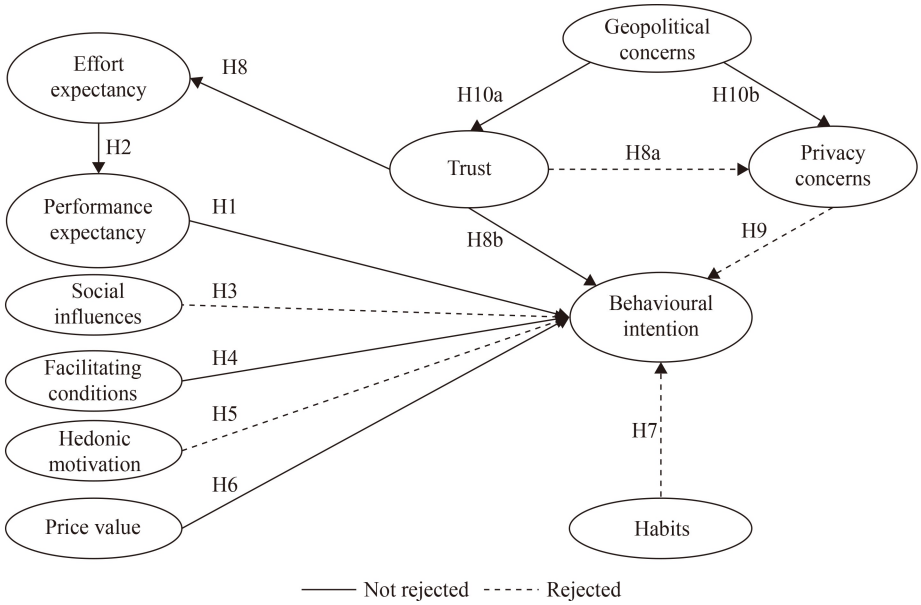

Figure 2 Summary of the research model.

Consequently, GenAI tools like DeepSeek are valued not for hedonic enjoyment but as practical instruments for gaining a competitive academic edge, with the stakes of performance heightened by the structural disadvantages these students face in the job market.

PV predicts the BI to use AI chatbots such as DeepSeek, thereby confirming H6. In Bangladesh, it appears that DeepSeek's open-source nature provides significant advantages. Indeed, a 25 USD monthly cost of a ChatGPT subscription can exceed 10% of the average monthly income, placing it well beyond the reach of ordinary users. For example, over 75% of respondents agreed or strongly agreed with the statement "DeepSeek provides excellent benefits without requiring a financial cost, unlike tools such as ChatGPT".

Remarkably, HB does not significantly predict the BI to use DeepSeek. In contrast with the results from other studies (Biloš & Budimir, 2024), HB appears to be more of a consequence of usage rather than a motivator for initial adoption.

The results indicate a multifaceted function of TR in influencing various aspects of AI chatbot adoption. H8a, which assumed that TR would have a positive effect on PC, was not supported. However, H8b was confirmed, which suggests that higher levels of trust positively contribute to higher BI. Most significantly, H8c was strongly supported, thereby indicating a strong correlation between TR and EE (Balaskas et al., 2025).

H9, which posited that PC influences the BI to use AI chatbots such as DeepSeek, was not supported. This suggests that privacy alone may not be a decisive factor. Despite a general unease towards privacy when using DeepSeek, particularly regarding the Chinese government's oversight and the potential misuse of personal data, these concerns might not be sufficiently strong to deter them from using DeepSeek. Unlike in Western countries, Bangladesh is a society of communities, not of individuals. Consequently, in a high-population-density country with limited personal space, Bangladeshi students prioritise the value of timely assistance and assignment completion over concerns for personal data security or surveillance.

Further, Hypotheses H10a and H10b were confirmed. Thus, it was also possible to confirm that geopolitical concerns have a positive direct impact on both TR and PC, thereby indirectly influencing the behavioural intention to adopt DeepSeek through these variables.

5.5 | Implications

The case of DeepSeek—a resource-constrained AI startup that has successfully disrupted a landscape dominated by well-funded counterparts—has critical implications for developing nations such as Bangladesh. Unlike OpenAI, which spends approximately 50 million USD monthly to operate ChatGPT, DeepSeek developed its advanced AI model, DeepSeek-V3, in under 6 million USD (DeepSeek-AI et al., 2024; DeepSeek-AI et al., 2025; Fernandes et al., 2025). By designing algorithms to run on low-cost, widely available hardware rather than expensive, high-end GPUs, DeepSeek reduced energy consumption by 40%.

For Bangladeshi policymakers and university administrators, the open-source nature of models such as DeepSeek provides a concrete mechanism to overcome critical infrastructure hurdles. Instead of sole reliance on expensive international cloud services, institutions can leverage publicly available model weights to develop localised, on-premises AI solutions. This strategy directly mitigates the challenges of internet unreliability, significantly lowers long-term operational costs, and enhances data sovereignty by ensuring sensitive academic data remains within national borders. A focused national strategy could prioritise the development of specialised, cost-effective computing clusters specifically designed for running and fine-tuning such open-source LLMs, thus creating a foundational pillar for indigenous AI development.

Concurrently, for global AI developers, our findings indicate the need for specific localisation requirements essential for success in markets such as Bangladesh. To move beyond broad technical adaptability, developers should prioritise three key areas: deep linguistic localisation that includes major regional dialects such as Sylheti and Chittagonian; the creation of lightweight model versions or streamlined applications that maintain core functionality during frequent low-bandwidth conditions; and active collaboration with local universities to fine-tune models based on Bangladeshi curricula and academic contexts, thereby directly increasing their perceived performance expectancy for students and educators.

This new wave of accessible AI innovation signals a broader geographic diversification of technological leadership. For Bangladesh, historically a provider of digital services, it represents a strategic opportunity to reassess its role in the global technology ecosystem. However, realising this potential requires overcoming structural obstacles, notably the brain drain of skilled IT professionals (Prome & Sultana, 2025). Policies that incentivise the return and engagement of diaspora researchers, particularly in projects focused on adapting open-source AI to local problems, are crucial. In the context of this globally distributed development of AI, Bangladesh stands at a crossroads. By pursuing a proactive national strategy that capitalises on open-source platforms, addresses specific local constraints, and builds strategic indigenous capacity, the country can transition from a peripheral user of technology to

an active hub for context-aware, high-value AI innovation in the Global South.

6 Conclusions

In conclusion, this study bridges the critical intersection of geopolitics and AI adoption to make information system studies more relevant to the present context. Bangladesh adopts a neutral-to-positive stance towards Chinese technology. This study reveals a paradox in Bangladesh's AI adoption landscape—despite the privacy-related concerns, Bangladeshi students are not only receptive to using DeepSeek but also consider it a valuable tool. Bangladeshi students embrace DeepSeek not merely for its cost-effectiveness but also because they view it as a culturally congruent technology that aligns with their nation's strategic partnerships with China and fosters a broader range of technological choices and reduces dependency on a single source of AI technology within the current ecosystem.

While DeepSeek enables local deployment and API-based customisation, the increasing dependence on foreign AI technologies prompts more general questions regarding technological self-reliance, digital sovereignty, and national security. To this end, the release of DeepSeek should serve as a call to action for South Asian nations to maximise their training and computing capacities and support the creation of indigenous AI solutions that are suited to the region's requirements.

Finally, this research paper has a few limitations. First, considering the sheer size of the population of Bangladesh, the sample size is limited. Second, the study focused on stated preferences rather than revealed preferences or actual behaviour with DeepSeek. Self-reported data may not entirely reflect real-world app usage. Therefore, future research should seek to extend the scope of analysis by focusing on other South Asian countries, particularly India and Pakistan.

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Conflicts of Interest The authors declare that they have no competing interests.

Ethics Statements Informed consent was obtained from all participants involved in this study. All participants were fully informed about the study's aims, procedures, and potential risks before agreeing to participate. Ethical approval for this study was granted by the CEOS.IPP Ethics Committee.

Data Availability Statements The authors confirm that all data generated or analyzed during this study are included in this published article.

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