Revisiting university students’ intention to accept AI-Powered chatbot with an integration between TAM and SCT: a south Asian perspective

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Abstract

Purpose – This paper aims to explore students’ intention to use and actual use of the artificial intelligence (AI)-based chatbot such as ChatGPT or Google Bird in the field of higher education in an emerging economic context like Bangladesh.

Design/methodology/approach – The present study uses convenience sampling techniques to collect data from the respondents. It applies partial least squares structural equation modeling (PLS-SEM) for analyzing a total of 413 responses to examine the study’s measurement and structural model.

Findings – The results explore that perceived ease of use (PEOU) negatively affects intention to adopt AI-powered chatbots (IA), whereas university students’ perceived usefulness (PU) influences their IA positively but insignificantly. Furthermore, time-saving feature (TSF), academic self-efficacy (ASE) and electronic word-of-mouth (EWOM) have a positive and direct impact on their IA. The finding also reveals that students’ IA positively and significantly affects their actual use of AI-based chatbot (AU). Precisely, out of the five constructs, the TSF has the strongest impact on students’ intentions to use chatbots.

Practical implications – Students who are not aware of the chatbot usage benefits might ignore these AI-powered language models. On the other hand, developers of chatbots may not be conscious of the crucial drawbacks of their product as per the perceptions of their multiple users. However, the findings transmit a clear message about advantages to users and drawbacks to developers. Therefore, the results will enhance the chatbots’ functionality and usage.

Originality/value – The findings of the study alert the teachers, students and policymakers of higher educational institutions to understand the positive outcomes and to accept AI-powered chatbots such as OpenAI’s ChatGPT. Outcomes also notify the AI-product developers to boost the chatbot’s quality in terms of timeliness, user-friendliness, accuracy and trustworthiness.

Keywords Artificial intelligence, Chatbot, ChatGPT, TAM, SCT, Bangladesh

Paper type Research paper

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Future research direction: The current study only focuses on investigating the university students’ behavioral intention toward the adoption of AI-powered chatbots. Furthermore, this paper only applies the original TAM research paradigm to integrate with SCT for developing the conceptual framework. Therefore, future researchers might emphasize more rigorous studies to explore university teachers’ behavioral responses toward adopting digital chatbots by applying extended TAM or unified theory of acceptance and use of technology (UTAUT).
1. Introduction
In the past 7 decades, scientists and scholars globally conducted groundbreaking researches on artificial intelligence (AI), which involves developing AI comparable to humans, utilizing computer and Internet technologies. AI significantly impacts various aspects of daily life, including the economy, healthcare, business, politics and education (Jiang et al., 2022). With the remarkable success of ChatGPT, AI has gained immense attention across platforms, emerging as a prominent research trend (Holzinger et al., 2023).

Academia is undergoing digital transformation, aligning with the fourth industrial revolution seen in healthcare, businesses and transportation. The focus now shifts to debating whether AI-based digital chatbots, like ChatGPT, are a curse or blessing for students and faculties. Developed by OpenAI, a San Francisco-based tech firm, ChatGPT evolves from version 3 to version 4 (Biswas, 2023).

As an emerging economic country, Bangladesh witnesses growing interest among students from various higher educational institutions in using ChatGPT since its release on November 30, 2022. However, no significant studies, especially in education, explored the intentions and actual use of ChatGPT among students in Bangladesh. To address these gaps, the present study aims to set objectives through data collection and analysis, requiring advanced strategic plans, tactics and policies for adopting new technologies like ChatGPT (Awal et al., 2023a, b). The developed objectives are as follows:

1. To explore the impact of socio-psychological factors [such as perceived ease of use (PEOU), perceived usefulness (PU), time-saving feature (TSF), electronic word-of-mouth (EWOM) and academic self-efficacy (ASE)] on university students’ intention to use AI-based chatbots (IA) in the context of Bangladesh.

2. To reveal the impact of university students’ intention to use AI-powered chatbots (IA) on the actual use of AI-based chatbots (AU) in the context of Bangladesh.

3. To validate the integration between the technology acceptance model (TAM) with social cognitive theory (SCT).

The outcome of this comprehensive work will certainly assist the developers of multiple chatbots such as ChatGPT or Google Bird to increase the functionality with the minimum time required to respond to complex queries.

2. Background study and theoretical underpinning

2.1 Chatbot foundation
Chatbots were developed in 1950 but in recent years tech firms have grabbed this natural language model to gain better insights into their target customers (Kaczorowska-Spychalska, 2019). As a hot trend, the present study chooses AI-powered chatbot (ChatGPT) as the study domain.

2.2 Technology acceptance model (TAM)
The TAM, developed by Davis (1989) and modified from Fishbein and Azen’s (1975) Theory of Reasoned Action, predicts users’ technology acceptance (see Figure 1). Davis introduced PEOU and PU as key predictors for investigating users’ behavioral attitude and intention to use new technology. PEOU reflects users expecting a hassle-free and user-friendly experience (Na et al., 2022), while PU signifies users anticipating significant opportunities and improved performance (Bailey et al., 2022). This study applies TAM to interpret and predict Bangladeshi university students’ intention and actual use of AI-based ChatGPT (Bin-Nashwan et al., 2023).
2.3 Social cognitive theory (SCT)
Rana and Dwivedi (2015) applied SCT to investigate users’ intentions in adopting new technologies like e-banking, e-government and digital platforms. SCT considered cognitive factors (self-efficacy, values), environmental factors and stress, impacting decision-making in accepting new technology (Bandura, 2023). This study examines TSF, ASE and EWOM as independent variables, exploring Bangladeshi university students’ behavioral intention and use of AI-based ChatGPT (Bin-Nashwan et al., 2023).

2.4 Integration between TAM and SCT
The present study uses TAM by Davis (1989) through an integration with SCT by Bandura (1986) to support the conceptual framework of the study. To the best of the author’s knowledge, no single study has utilized the integration of TAM and SCT to investigate the intention and real-world application of AI-based ChatGPT by university students in Bangladesh and around the world. Meanwhile, this novel theoretical integration was applied to reveal the clients’ mobile banking adoption intention and actual use (Hajiyev and Chang, 2017). Theories centered on human behavior suggest that an individual’s inclination to engage in a particular action or embrace a new aspect is influenced by psychological, behavioral, environmental and cognitive factors related to their lifestyle. So, the literature rationally supports and positively validates the integration between TAM and SCT to conduct comprehensive research on exploring students’ ChatGPT adoption intention and actual use (Davis, 1989; Lee et al., 2023).

2.5 Perceived ease of use (PEOU) and intention to adopt AI-based chatbot
As per Davis (1989), perceived ease of use (PEOU) entails users’ perceptions of how effortless it is to utilize a new technology or system, aiming for minimal effort. Hamidi and Chavoshi (2018) asserted that researchers are deeply engaged in pioneering research and experiments to simplify people’s lives by creating innovative technology employing computers and information systems. Meanwhile, a comprehensive study by Tiwari et al. (2023) revealed a highly paradoxical result that PEOU has no significant positive impact on students’ adoption intention of AI-based ChatGPT. Hence, given the mixed outcomes in this field, a more comprehensive investigation is deemed necessary. Consequently, the authors posit the following correlation between PEOU and the inclination to adopt AI-based ChatGPT, aiming to elucidate the unresolved paradox.

H1. PEOU does not positively influence the university students’ behavioral IA.

2.6 Perceived usefulness (PU) and intention to adopt AI-based chatbot
PU as one of the constructs of TAM transparently depicts the system users’ degree of trust that a newly developed system might boost the effectiveness, performance and quality of their job (Davis, 1989). Numerous prior studies have delved into examining the impact of PU on users’ behavioral intentions to adopt technology. According to Astuti (2023), the
extent of belief among bank clients in the utility of adopting Internet banking serves as a reliable predictor for their inclination to use i-banking. Therefore, the authors accept that university students' IA highly depends on their PU. Thus, this study posits the following association between PU and students’ behavioral IA as the second hypothesis of the current study:

**H2.** PU significantly influences the university students' behavioral IA.

### 2.7 Time-saving feature and intention to adopt AI-based chatbots

In the era of Industry 4.0, time is considered the most precious resource, as individuals feel compelled to complete multiple tasks within a 24-h period. Martha (2009) highlighted that human psychology, particularly the perception of using time effectively, efficiently and significantly influences behavior and related intentions in social and environmental contexts. Ng *et al.* (2023) further emphasized that the adoption intention of technology users is significantly shaped by the timely features associated with using technology. Therefore, the current study spells out based on the above-discussed literature, university students and faculty members might display positive intention to accept AI-based chatbots of chatbot’s timeline feature. Thus, this study posits the following hypothesis:

**H3.** TSF positively influences the university students' behavioral IA.

### 2.8 Electronic word-of-mouth (EWOM) and intention to adopt AI-based chatbot

EWOM is the online expression of reviews and unbiased opinions on products or services by experienced customers, aiding new buyers on platforms (Li *et al.*, 2022). Literature on EWOM’s direct impact on students’ AI-based chatbot adoption is limited. Previous studies focused on EWOM’s influence on trust, perception, satisfaction and buying attitude (Kusawat and Teerakapibal, 2022). Bin-Nashwan *et al.* (2023) found a positive impact of chatbot users’ EWOM on their willingness to adopt AI-based chatbots like OpenAI’s ChatGPT for academic and non-academic tasks. However, more rigorous studies are needed for stronger theoretical evidence, addressing queries of readers, academics and policymakers. This study posits a hypothesis on the relationship between EWOM and the IA.

**H4.** EWOM positively influences the university students' behavioral IA.

### 2.9 Academic self-efficacy and intention to adopt AI-based chatbot

Self-efficacy, akin to self-confidence, reflects one’s belief in their ability. Academic self-efficacy gauges a student’s confidence in task performance or learning new material (O'Connor and Mahony, 2023). ChatGPT’s launch transformed academic approaches, offered continuous support for information retrieval and problem-solving, enhanced self-efficacy for both teachers and students (Rudolph *et al.*, 2023). Additionally, Bin-Nashwan *et al.* (2023) noted a positive link between academic self-efficacy and users’ intention to use AI-based ChatGPT.

Therefore, the present study develops the following relationship as the hypothesis of the current study:

**H5.** Academic self-efficacy positively influences the university students’ behavioral IA.

### 2.10 Intention to adopt AI-based chatbot and actual use of chatbot

The acceptance of new elements by users is steered by their behavioral intention and the actual usage serves as the manifestation of those intentions. Current research underscores the
positive influence of behavioral intention on the utilization of systems. Raman et al. (2022) found a positive link between users’ adoption intention and actual usage in a study on learning management systems. Similarly, Awal et al. (2023a, b) discovered online customers’ future buying willingness influenced belief in fraudulent news. This study endeavors to fill the existing gap in comprehending the connection between university students’ inclination to utilize AI-based chatbots and their real usage. The hypothesis formulated for investigation is as follows:

H6. IA positively influences the university students’ AU.

The study explores global perspectives on AI-powered chatbots, revealing challenges identified by Lin et al. (2023) in a 23-year systematic review. Key issues include aligning user queries with language models for precise answers and ensuring user readiness for AI-powered chatbots (Chhibber and Bhadauria, 2022).

The literature review reveals clear gaps in understanding: mixed results on PEOU’s impact on students’ AI-powered chatbot adoption intention, a country gap in Bangladeshi context, a theoretical gap in TAM-SCT integration and a lack of studies on the consequence of adoption intention on actual usage. This study proposes a research model addressing these gaps (see Figure 2).

Uniqueness is highly required for all kinds of research, whether it may be from the social science domain or any other domain. The present study has a particular uniqueness since it blends two renowned theoretical paradigms including TAM and SCT to investigate the students’ willingness to accept and use AI-powered chatbots for the very first time.

3. Methodology

3.1 Sampling frame and survey instrument

The study utilizes convenience sampling as like other social science researches (Alam, 2022). This non-probability technique involves selecting easily accessible and communicative respondents (Liu et al., 2022). The research targets university students in Bangladesh who have used an AI-powered chatbot like ChatGPT at least once. Major universities in Bangladesh like, Dhaka University, Rajshahi University, North South University and Bangladesh Army University of Science and Technology are included for conducting the survey. Survey instruments are developed based on existing literature, with most items

![Figure 2. Proposed research model based on TAM and SCT](image-url)

Source(s): Authors’ own creation
adopted and a few adapted for relevance. The questionnaire, designed with five-point Likert scales, measures latent variables and aligns with the study’s domain.

3.2 Validity of research instruments
The author engaged a psychometrician to ensure the questionnaire’s error-free construction in the psychometric assessment (Kumar et al., 2021). Expert opinions validated research instruments across multiple study dimensions. The questionnaire, aligned with a conceptual benchmark, received feedback from 5 domain experts to assess depth and rationality of items. Pilot testing (Mathews et al., 2023) involved 50 university students, refining the questionnaire based on expert recommendations and respondent observations, confirming face validity (Hock et al., 2023).

3.3 Data collection and respondents’ profile
Table 1 presents student profiles selected for the study, detailing gender, age, academic year and institution. The author distributed questionnaires via email, WhatsApp and social media platforms from January to March 2023, receiving 420 responses. After data cleaning, 413 finalized responses were used for inferential analysis on the conceptual framework’s measurement and structural models.

3.4 Common method bias test
The study uses self-administered questionnaires to gather responses on exogenous and indigenous variables. Therefore, it assesses common method bias (CMB) using Harman’s Single Factor test (Podsakoff and Organ, 1986; Elsayed, 2023). Fuller et al. (2016) and Saxena et al. (2022) suggest suitability for statistical analysis if variance is <50%. Analysis indicates a 31.21% variance in the data set, making the screened 413-sample data bias-free for valid statistical analysis.

4. Data analysis
4.1 Analysis of measurement model
The study utilizes SPSS-25 for initial data cleaning and employs SmartPLS 4.0.9.2 for descriptive and inferential analysis using PLS-SEM modeling. SPSS is preferred for data cleaning, as it excels in identifying monotonous responses, handling missing values and

<table>
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<th>Profile dimensions</th>
<th>Respondents’ characteristics</th>
<th>Participants (n = 413)</th>
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</thead>
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<tr>
<td></td>
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<td>Bangladesh Army University of Science and Technology</td>
<td>95</td>
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</table>

Table 1. Respondents’ information

Source(s): Authors’ own creation
testing data distribution (Roni and Djajadikerta, 2021). The research then utilizes PLS-SEM to examine the reliability, validity and hypotheses of a complex model, acknowledging its utility in differential psychology research with small sample sizes (Willaby et al., 2015).

4.1.1 Ensuring reliability and validity. 4.1.1.1 Goodness of fit measurement. Table 2 explores that the cleaned-up data set is perfectly fit for analysis with PLS-SEM since it meets the threshold value. The analytical results show that the standardized root mean square residual (SRMR) of the estimated model is 0.071 which is less than the threshold of 0.08 (Schuberth et al., 2022) and the normed fit index (NFI) is 0.953 which is very adjacent to 1 (Lohmöller, 1989).

4.1.1.2 Reliability and validity. Table 3 presents crucial metrics assessing the measurement model’s robustness. It evaluates internal consistency, multicollinearity and convergent validity through factor loadings, variance inflation factor (VIF), composite reliability (CR), average variance extracted (AVE) and Cronbach’s alpha (CA). Bagozzi and Yi (1988) suggested a factor loading range of 0.70–0.94 for effective latent variable measurement. The finalized items, meeting this criterion, are displayed in Table 3. VIFs, all below 5, confirm an absence of multicollinearity (Hair et al., 2013). CR and CA, gauging model reliability, surpass the threshold of 0.70. AVE, indicating convergent validity, exceeds 0.50 (Hair et al., 2013, 2020). Table 3 asserts that all criteria are met, affirming the model’s reliability and convergent validity. These outcomes also affirm the measurement model’s suitability for the structural model in the study.

4.1.1.3 Discriminant validity. This study assesses measurement model discriminant validity using Fornell–Larcker criterion and Heterotrait-Monotrait ratio (HTMT) – Matrix. Table 4 indicates latent variable AVEs exceed inter-correlations (Fornell and Larcker, 1981). According to Henseler et al. (2014), all constructs in Table 5 meet the HTMT criterion’s 0.9 threshold, confirming discriminant validity.

4.2 Analysis of structural model
The present study applies a bootstrapping PLS-SEM calculation technique based on a 5000 resampling strategy to verify the direct relationship among latent variables (Hair et al., 2021; Sarstedt et al., 2014; Alsyouf et al., 2023). Figure 3 shows the graphical representation of structural equation modeling.

The study utilized partial least squares-structural equation modeling (PLS-SEM) to test six hypotheses, as detailed in Table 6. Hypothesis 2 was the only one rejected, with PU not significantly influencing IA ($\beta = 0.009, \text{Std Error } = 0.011, t = 0.870, p = 0.384$). Hypotheses 1, 3, 4, 5 and 6 were accepted. PEOU negatively impacted IA ($\beta = -0.035, \text{Std Error } = 0.010, t = 3.508, p = 0.00$). TSF, EWOM and ASE positively influenced IA, with $\beta$ values of 0.514, 0.278 and 0.267, respectively. IA, in turn, positively impacted AU ($\beta = 0.579, \text{Std Error } = 0.035, t = 16.70, p = 0.00$). These results support the study’s structural model conclusions.

The study’s conclusions meet the criterion of $R^2 > 0.02$ in order to confirm the data set’s predictability of the dependent variable with the direct impact of independent variables

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**Table 2.** Goodness-of-fit index

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Students’ intention to accept AI-based chatbot
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<th>Latent variable and sources</th>
<th>Items</th>
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<th>CR</th>
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<td>N/A</td>
<td>0.895</td>
<td>0.809</td>
<td>0.765</td>
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<tr>
<td>Li (2023)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>AU02</td>
<td>0.908</td>
<td>1.621</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>AU03</td>
<td>0.891</td>
<td>1.621</td>
<td></td>
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<tr>
<td>AU04</td>
<td>Delete</td>
<td>N/A</td>
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</table>

**Table 3.**
Convergent validity, internal consistency and multicollinearity

**Note(s):** FL- Factor loading; AVE- Average variance extracted; CR- Composite reliability and CA- Cronbach’s alpha

**Source(s):** Authors’ own creation

<table>
<thead>
<tr>
<th>ASE</th>
<th>AU</th>
<th>EWOM</th>
<th>IA</th>
<th>PEOU</th>
<th>PU</th>
<th>TSF</th>
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<tbody>
<tr>
<td>0.799</td>
<td>0.507</td>
<td>0.691</td>
<td>0.932</td>
<td>0.497</td>
<td>0.716</td>
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<td>0.900</td>
<td>0.775</td>
<td>0.579</td>
<td>0.552</td>
<td>0.577</td>
<td>0.686</td>
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<td>0.806</td>
<td>0.863</td>
<td>0.534</td>
<td>0.757</td>
<td>0.498</td>
<td>0.978</td>
<td>0.906</td>
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</table>

**Table 4.**
Fornell-Larcker criterion

**Note(s):** PEOU- Perceived ease of use; PU-Perceived usefulness; TSF- Time-saving feature; EWOM- Electronic word-of-mouth; ASE- Academic self-efficacy; IA- Intention to adopt AI-powered chatbot; AU- Actual use of chatbot

**Source(s):** Authors’ own creation
This result shows that IA, as an independent variable, has predictability for AU and that all five exogenous variables successfully predict IA, an endogenous variable. Additionally, the PLS-SEM study results validate that the model can be predicted because

(see Figure 4). This result shows that IA, as an independent variable, has predictability for AU and that all five exogenous variables successfully predict IA, an endogenous variable. Additionally, the PLS-SEM study results validate that the model can be predicted because

<table>
<thead>
<tr>
<th>ASE</th>
<th>AU</th>
<th>EWOM</th>
<th>IA</th>
<th>PEOU</th>
<th>PU</th>
<th>TSF</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.640</td>
<td>0.811</td>
<td>0.776</td>
<td>0.751</td>
<td>0.783</td>
<td>0.804</td>
<td>0.682</td>
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<tr>
<td>0.876</td>
<td>0.583</td>
<td>0.822</td>
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<td>0.692</td>
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<tr>
<td>0.871</td>
<td>0.694</td>
<td>0.812</td>
<td>0.837</td>
<td>0.719</td>
<td>0.897</td>
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</tr>
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</table>

Note(s): PEOU- Perceived ease of use; PU-Perceived usefulness; TSF- Time saving feature; EWOM- Electronic word-of-mouth; ASE- Academic self-efficacy; IA- Intention to adopt AI-powered chatbot; AU- Actual use of chatbot

Source(s): Authors’ own creation

**Hypotheses Paths**

<table>
<thead>
<tr>
<th>Hypotheses</th>
<th>Paths</th>
<th>Beta (β)</th>
<th>Std. Error</th>
<th>t-value</th>
<th>p-value</th>
<th>Status</th>
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</thead>
<tbody>
<tr>
<td>H1</td>
<td>PEOU→ IA</td>
<td>-0.035</td>
<td>0.010</td>
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<td>H2</td>
<td>PU→ IA</td>
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<td>0.011</td>
<td>0.870</td>
<td>0.384</td>
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<tr>
<td>H3</td>
<td>TSF→ IA</td>
<td>0.514</td>
<td>0.031</td>
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<td>0.000</td>
<td>Supported</td>
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<tr>
<td>H4</td>
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<td>0.015</td>
<td>18.74</td>
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<td>Supported</td>
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<tr>
<td>H5</td>
<td>ASE→ IA</td>
<td>0.267</td>
<td>0.027</td>
<td>9.73</td>
<td>0.000</td>
<td>Supported</td>
</tr>
<tr>
<td>H6</td>
<td>IA→ AU</td>
<td>0.579</td>
<td>0.035</td>
<td>16.70</td>
<td>0.000</td>
<td>Supported</td>
</tr>
</tbody>
</table>

Note(s): PEOU- Perceived ease of use; PU-Perceived usefulness; TSF- Time saving feature; EWOM- Electronic word-of-mouth; ASE- Academic self-efficacy; IA- Intention to adopt AI-powered chatbot; AU- Actual use of chatbot

Source(s): Authors’ own creation

Table 5. Heterotrait-monotrait ratio (HTMT) - Matrix

Table 6. Results for hypothesis testing
they meet the $f^2 > 0.00$ threshold (refer to Figure 4). Consequently, this indicates that the data set and the model are a perfect match (Bin-Nashwan et al., 2023).

5. Discussion
The analysis part of the study reveals that PEOU significantly but negatively affects IA, which offers strong support for hypothesis 1. The existing literature in this domain explored the same outcomes where university students’ PEOU has a negative influence on their IA (Liu and Ma, 2023). This finding strongly suggests that university students’ perception regarding the easiness of using AI-powered digital chatbots does not determine their inner intention to use chatbots. The result of the study also explores that PU insignificantly affects IA which offers rejection for hypothesis 2. This finding does not completely match with existing findings since the literature denotes that students’ perception of the benefits of adopting AI-powered chatbots significantly determines their intention to use them (Chocarro et al., 2023). The analysis part of the study reveals that TSF positively and significantly affects IA, which gives acceptance for hypothesis 3. The previous studies also explored the parallel result in this field where TSF is regarded as a positive determinant of IA (Bin-Nashwan et al., 2023). On the other hand, findings display that EWOM affects IA positively, which provides support for hypothesis 4. The same findings were confirmed through previous studies in this domain where the authors found that EWOM has a significant positive impact on students’ IA (Bin-Nashwan et al., 2023; Kusawat and Teerakapibal, 2022). The PLS-SEM result transparently denotes that ASE as the model’s independent variable has a positive and statistically significant impact on IA, which then offers acceptance for hypothesis 5. Meanwhile, this finding is also supported by existing literature where the researchers obtained a positive and significant influence of ASE on IA (Rudolph et al., 2023; Bin-Nashwan et al., 2023).

Finally, the statistical result from PLS-SEM informs us that IA has the strongest impact on AU, which provides support for hypothesis 6. Existing literature (Ni and Cheung, 2023; Li, 2023; Rukhiran et al., 2023) verifies the result of this study by exploring IA as the significant predictor to determine AU.

5.1 Theoretical implications
The present study contributes theoretically to this domain by comprehensively expanding the existing literature. To the best of the author’s knowledge, widely applied TAM and SCT...
research paradigms are integrated to create a new theoretical path for the very first time in this study which will create an opportunity for future research in this domain. Furthermore, this study might effectively enhance the readers’ knowledge about the pros and cons of the TAM and SCT to understand the university students’ intention and actual use of AI-powered digital chatbots such as ChatGPT. Previously, TAM and SCT were applied to investigate behavioral responses separately. Therefore, this study develops a new foundation undoubtedly based on the integration between TAM and SCT to investigate students’ behavioral intentions and consequences in the field of AI.

5.2 Managerial implications
The study’s results highlight key insights beneficial for policymakers, users and communities. Notably, time-saving features in digital chatbots significantly influence university students’ adoption intentions. This insight aids developers in enhancing future chatbot versions, emphasizing efficiency. Tailoring products to student preferences fosters widespread acceptance globally. Additionally, the study assists universities in understanding students’ behavior influenced by cognitive and environmental factors. Promoting awareness of AI-powered chatbot benefits increases adoption rates, such as with ChatGPT. The findings deliver a crucial message to the student community, particularly in higher education, potentially amplifying their inclination to use AI-powered chatbots based on the study’s outcomes.

5.3 Knowledge implications
The findings significantly impact understanding technology adoption in education. It highlights AI’s evolving role, emphasizing AI-powered chatbots as crucial student support tools. The study provides insights into factors influencing student acceptance, aiding educators and developers in enhancing user experience. Exploring students’ intentions contributes to the broader discourse on human-AI interaction, unveiling trust and acceptance intricacies in educational technology. The findings guide educational institutions in seamlessly integrating AI-powered chatbots, fostering a positive student-technology relationship.

References


Further reading


Corresponding author
Md. Rabiul Awal can be contacted at: rabiul.ru.mgt18@gmail.com

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Students’ intention to accept AI-based chatbot

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