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Impact of AI in Education: An Evidence from Use of ChatGPT in Management Education in Nepal

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Abstract

Purpose: The purpose of the study is to examine the impacts of ChatGPT in management education in the Nepalese educational landscape.

Methods: An explanatory research design was used in this study. Four hundred-three respondents were taken as a sample using the convenience sampling method. Technology Acceptance Theory is used. Descriptive and inferential statistics were used to examine the data. SEM was used to analyse the data.

Findings: The results show that perceived ease of use, usefulness, and attitude significantly affect behavioural intention. Accuracy and reliability, data privacy, and security are significant challenges faced by the user, and the managerial solution for reducing these challenges is to follow proper rules and regulations, as well as safety and security measures.

Conclusions: This study concludes that behavioural intention towards ChatGPT is affected by perceived ease of use, usefulness, and attitude.

Implications: This analysis and findings will help the Ministry of Communication and Information Technology, an educational institution, IT agencies, the government, researchers in similar fields, professionals, and future students.

Originality: This research is original, and there is no knowledge conflict.

Keywords: Technology Acceptance Theory, ChatGPT, management education, Structural Equation Modeling

JEL Classification: B16, B23, C12, C83, O32, O36, I23

1. Introduction

Artificial intelligence (AI) refers to developing computer systems that can perform tasks typically requiring human intelligence. These tasks include understanding natural language, recognising patterns, solving complex problems, making decisions, and learning from experience. Furthermore, efficiently and adaptively, leading to advancements in various fields such as healthcare, education finance, manufacturing, and more (Ray, 2023). AI is a technology that's useful for humans. It can help to avoid doing complex tasks. It can be used in healthcare, education, electronics, making software, pharmacies, playing games, engineering, communication, and creating new things. It is like a tool that makes our lives easier and better.

The rapid development and integration of artificial intelligence (AI) and machine learning technologies have led to transformative changes across various industries, including higher education. It has considerably impacted the education sector (AIEd), particularly in administration, instruction, and learning (L. Chen et al., 2020). Universities are now exploring ways to harness AI's power to enhance the student experience and support faculty in their teaching and research efforts (Zawacki-Richter et al., 2019)Artificial Intelligence in Education (AIEd. The emergence and urgency of artificial intelligence have been driven by the COVID-19 pandemic's impact and a growing emphasis on real-time computing needs (Lim et al., 2022). Another popular language model is being used in higher education. Other well-known language models include Google Bard, ChatGPT (Generative Pre-trained Transformer), GPT-2, and RoBERTa. All of these AI models have the potential to revolutionise teaching, learning, and research in higher education, but they vary in their strengths and limitations (Atlas, 2023). Since late November 2022, there has been a rapid acceleration in the chatbot field, marked by intense competition among various chatbots in an AI arms race, significantly impacting higher education, where a multitude of students and academics are embracing bots like ChatGPT, Bing Chat, Bard, Ernie, and others across diverse applications(Rudolph et al., 2023). Some recent generative artificial intelligence programs include ChatGpt and Berd being the most discussed technological innovations (Dwivedi et al., 2023). In the past few years, technology has improved a lot, and one of the big advancements is ChatGPT, which is a significant AI language model (Ray, 2023).

ChatGPT's implementation in the classroom positively impacts the teaching-learning process. Technological innovation has become essential in a constantly changing society and has inevitably left its mark on education. ChatGPT's implementation in the classroom positively impacts the teaching-learning process. OpenAI's innovation, ChatGPT, is revolutionising the learning process. By tailoring activities and content to each student's unique needs, this tool enhances the efficacy of teaching and learning. Furthermore, learning becomes more customised and individualised, which raises student motivation and commitment levels (Montenegro-Rueda et al., 2023)based on a systematic review of the literature, an analysis of the impact of the application of the ChatGPT tool in education. The data were obtained by reviewing the results of studies published since the launch of this application (November 2022.

Baidoo-Anu and Owusu Ansah (2023) stated that ChatGPT can be an effective educational tool by providing personalised tutoring, automated essay grading, language translation, interactive learning, and adaptive learning. While there are many potential benefits of using ChatGPT and other generative AI models in education, there are also some drawbacks: lack of human interaction, limited understanding, lack of creativity, dependency on data, privacy, and limited ability to personalise instruction. ChatGPT faces numerous issues while implementing it in the education sector. Some of the challenges are plagiarism, biased content, misinformation, hallucination, i.e., creating new data or information which does not exist (Deng and Lin, 2022), misinformation (Borji, 2023), not real-time access, ethical issues, and over-reliance(Sohail et al., 2023).

Thus, the purpose of this study is to study the impact of ChatGPT on management education, which can help enhance innovative technology and aid in developing alternative feasible strategies for overcoming the challenges faced by users. Furthermore, few studies are related to AI in Nepal, so this study will help other scholars, researchers, educators, and students know more about AI's impact on the earning process.

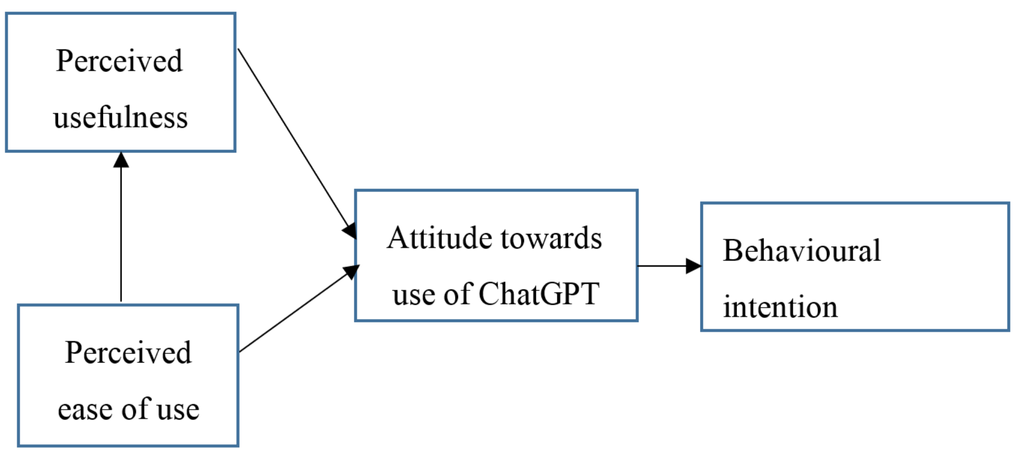
2. Conceptual Framework and Hypothesis Formulation

In this study, several established theories were examined, including the Technology Acceptance Theory (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), Community of Inquiry (CoI), Technology Enhanced Learning (TEL), and Diffusion of Innovation Theory (DOI). These theories offer insights into learners' intentions, perceived usefulness, and behaviour changes in response to technology. According to TAM theory, the perceived usefulness and ease of use components significantly impact students' intentions to utilise ChatGPT technology (Shaengchart, 2023). Perceived usefulness and perceived ease of use aim to promote technology adoption and enhance students' overall learning experience, influencing students' intent to adopt ChatGPT technology. Performance expectation, effort expectation, social influence, and facilitating conditions are the four primary factors that UTAUT focuses on. It forecasts technology's success by comprehending the factors that influence its adoption. (Ammenwerth, 2019). Age and experience can also moderate the impact of various factors on the use of ChatGPT (Menon & Shilpa, 2023). According to the Community of Inquiry (COI) Theory, learning experiences will be facilitated through three presences: cognitive presence, social presence, and teaching presence. It shows the causal relationship between teaching, social presence, and cognitive presence that supports learning and helps students develop a strong sense of community(Fiock, 2020). Technology Enhanced Learning (TEL) states that technology enhances the learner's experience. It makes it possible to create new kinds of learning that are more tailored to the needs of specific students, enhance the platforms for contextual learning, and bridge the gap between formal and informal learning environments (Habib & Johannesen, 2020). According to Diffusion of Innovation Theory (DOI), diffusion is the process by which an innovation spreads over time. It examines the potential adoption of new technologies by following five steps: learning, convincing, deciding, using, and confirming. It comprises the basic elements of innovations, adopters, and communication channels, serving as a foundational framework for understanding AI adoption (Apleni & Smuts, 2020).

The development of this conceptual framework was grounded in the Technology Acceptance Model. The relationship explained by this theory is shown in the following diagram.

Figure 1

Conceptual Framework



Sources: Adapted from Liu and Ma (2023)

Perceived Ease of Use and Perceived Usefulness

Ease of use decreases user error by adopting a technology (Windasari et al., 2022). Both usefulness and ease of use are fundamental determinants of user acceptance. Additionally, the TAM suggests that individuals accept information technology if they believe in its positive performance, increasing the tendency to use it frequently. Perceptions of usage and perception of ease of use are important factors that influence system use. The perceptions of usefulness were more substantial and more consistent with the acceptance of information technology than other variables, such as attitudes, satisfaction, and other perceptual measures (Machdar, 2019).

H1: Perceived usefulness is associated with perceived ease of use.

Perceived Usefulness and Attitude

Perceived usefulness is the degree to which individuals believe using a particular system would enhance their capacity to perform their duties (Lim & Benbasat, 2000). Attitude is a person's positive or negative feelings about performing the target behaviour (Elkaseh et al., 2016)—a recent research by Y. L. Chen et al. (2015) state that attitudes toward the use of online ordering platforms by securities brokers can be favourably impacted by perceived usefulness. A study (Sentosa, 2012) has provided empirical evidence that perceived usefulness significantly and positively impacts attitudes toward using information technology or related systems.

H2: perceived usefulness is associated with attitude

Perceived Ease of Use and Attitude

According to Fishbein and Ajzen (1975), attitude towards actual usage is determined by an expectancy of how easily the user thinks he can use the system. TAM posits that PEOU has a direct positive effect on attitude towards using the system. The complexity of one particular system will become the inhibitor that discourages adopting an innovation (Rogers, 2014). The existing studies suggest that perceived ease of use is a significant attribute in determining an individual's attitude toward system usage. PEOU is also hypothesised to affect attitude significantly (Fred D. Davis, 2010).

H3: Perceived ease of use is associated with attitude.

Attitude and Behavioural Intention

Behavioural intention is characterised as a behaviour prior to an action being taken. It is a pattern or influence that motivates someone to form a habit. According to Rhema et al. (2010), various factors, such as users' attitudes toward e-learning and their level of satisfaction with using technology during the teaching/learning process, influence the success of e-learning. Intentions show what drives an action and how much effort a person will put forth to carry it through. Strong intentions make a behaviour more likely to be carried out, but they only work if the behaviour is voluntarily chosen to be performed. The effectiveness of conduct is also influenced by non-motivating factors like the accessibility of resources (Ajzen, 2022).

H4: Attitude is associated with behavioural intention.

Perceived Ease of Use, Perceived Usefulness, Attitude and Behavioural Intention

Perceived ease of use and students' intention to use virtual learning Students' intentions can be influenced by their attitudes, and attitudes play a critical role. There is a relationship between students' attitudes and their willingness to use online learning platforms. Users prefer online learning because it is simple and improves their performance and knowledge. Users' attitudes are primarily motivated by perceived ease of use, according to Cheng and Chen (2011). It implies that perceived ease of use (PEU) influences people's attitudes toward online learning. Users' opinions and the ease of use of online learning are measured by PEU (Zahir Osman et al., 2012). In a study by Kanchanatanee et al. (2014), the impact of small and medium-sized business owners' attitudes toward using E-Marketing is defined by their perceptions of its usefulness, ease of use, and compatibility on their intention to use it. Attitude toward using E-Marketing is the most important factor influencing the intention to use Online Promotion.

Based on the above-mentioned hypothesis, the hypothesis of attitude as mediation could be formulated as:

H5: perceived ease of use significantly impacts behavioural intention with attitude as mediation.

H6: perceived usefulness significantly impacts behavioural intention with attitude as mediation.

Variable and Definitions

Table 1

Variables Table

Constructs	Indicators	Variables	Details
Perceived Usefulness	Pu1	quickly	Helps me to find the information I need quickly and easily.
	Pu2	Valuable	A valuable resource for providing information related to my studies.
	Pu3	Ability	Enhance my ability to learn.
	Pu4	Confident	feel more confident in completing my assignments with the help of ChatGPT
	Pu5	Accurate	Find ChatGPT's responses to be accurate and reliable.
Perceived ease of use	Peu1	Use	Easy to use.
	Peu2	Want	Easy to get ChatGPT to do what I want it to do.
	Peu3	Comfortable	Comfortable using ChatGPT for various educational tasks.
	Peu4	Interaction	Interaction with ChatGPT is clear and understandable.
	Peu5	User-friendly	User-friendly AI tool.

Attitudes towards to use ChatGPT	Atuc1	Enjoy	Enjoy using ChatGPT.
	Atuc2	Fun	Using ChatGPT is fun.
	Atuc3	Interact	interesting to interact with ChatGPT
	Atuc4	Privacy	concerned about the privacy of my information when using Chat GPT
	Atuc5	Enhance	Using ChatGPT enhances my online experience.
Behavioural intention to use ChatGPT	Bi1	Intend	Intend to use ChatGPT in future.
	Bi2	plan	Plan to use Chat GPT frequently in the future.
	Bi3	Expect	Expect to use ChatGPT more often in the future than I do now.
	Bi4	Worth	Worth it to use ChatGPT.
	Bi5	Educational information	Tell others to use educational information ChatGPT.

Source: Yilmaz et al. (2023)

3. Research Methods

Study Area and Population

The Kathmandu Valley has been selected as the research area. Three districts make up the Kathmandu Valley: Kathmandu, Lalitpur and Bhaktapur. According to Mohanty (2011), the Kathmandu Valley is 1,300 meters above sea level and is situated between 27°32'13" and 27°49'10" north latitude and 85°11'31" and 85°31'38" east longitude. The three valley districts are 665 square kilometres (Adhikari et al., 2024). The number of AI users in Nepal, particularly in the Kathmandu Valley, is increasing. Kathmandu Valley is densely populated, with over 3.1 million people living there, per the Data portal in 2023. The primary motivation behind picking this topic is to study the impact of ChatGPT and students' behavioural intentions towards it. Many people or things that are the focus of a scientific investigation are referred to as a research population. The population for which data is gathered is known as the target population. Everyone who uses AI tools for their study is regarded as the population for this study.

Sampling Technique

The study's population is unclear, making the non-probability sampling technique suitable for this research. Convenience sampling is a nonprobability or nonrandom sampling in which participants of the target population who fit specific practical requirements such as being easily accessible, nearby, available at a specific time, or willing to participate are included in the study (Etikan, 2016; Singh et al., 2024). This study uses convenience sampling, which is a non-probability sampling technique.

For sample size calculation, $n_0 = z^2 pq / e^2$ formula is used where n= sample size required for study, standard tabulated value for 5% level of significance (z) = 1.96, p=prevalence or proportion of an event 50%=0.50. So, P= 0.5 and q=1-p, =0.5. The allowable error that can be tolerated (e) = 5%. So, total population for the study $n_0 = z^2 pq / e^2 = (1.96)\ 2 \times 0.5 \times 0.5 / (0.05)\ ^2 = 384.16$. Non-response error 5%, i.e., 384.16*5/100=19.21, is also included. Thus, the sample size needed for the study was (384.16+19.21) = 403.36(~403).

Data Collection and Analysis

This study used a structured questionnaire and interviews as the primary research tool. A structured questionnaire on the impact of ChatGPT on management education has been designed to gather data. To accomplish the numerous goals outlined above for the study, the researchers have linked questionnaires. The researcher's attention was next toward the questionnaire's sequencing and arrangement. In the KOBO toolkit, the structured questionnaires that have been developed are used to collect data. The questionnaire was administered into the KOBO Toolbox to evaluate the instrument's consistency and correctness.

Data analysis is done as soon as is practical after the data have been acquired, both when the researcher is still in the field and later when the researcher is no longer in the field (Kawulich 2015). Data analysis used structural equation modelling and descriptive, as well as inferential analysis based on various latent constructions. Software such as KOBO Toolbox, Microsoft Excel and PLS-SMART 4.0 were used for data analysis, while Microsoft Excel was used for data entry and tabulation.

4. Result And Analysis

Social-Demographic Characteristics

Table 2

Socio-Demographic Analysis

Title	Category	Number	Percentage (%)
Gender	Male	207	50.51%
	Female	212	49.49%
Age	Less than 25	28	6.41%
	26-30	210	48.05%
	31-35	66	15.1%
	36-40	109	24.94%
	Above 40	24	5.49%
Education Level	Intermediate	56	12.81%
	Undergraduate	137	31.35%
	Graduate	142	32.49%
	Postgraduate	102	23.34%
Location	Kathmandu	264	60.41%
	Lalitpur	123	28.15%
	Bhaktapur	50	11.44%

Table 2 shows the socio-demographic variables; 403 respondents were surveyed to identify the behaviour intention of students towards the use of ChatGPT, where the majority of respondents are males, i.e., 50.51%, and the remaining 49.49 % are female. Nevertheless, in a similar study, the majority of respondents were female, i.e. 81.97% and male respondents were 18.02% (Liu & Ma, 2023). The largest group of respondents consist of 210 respondents aged 26-30 years, accounting for 48.05% of the total respondents. The next largest age group is 36-40, with 109 respondents. The 31-35 age group represents 15.1% of the respondents (66 individuals), followed by the age group less than 25 (6.41%), and a small percentage of respondents are above 40 years (24 individuals). This implies that a significant proportion of the participants belong to the middle-aged adult demographic, aligning with a study conducted by (Yilmaz et al., 2023; Bonsu & Baffour-Koduah, 2023). Considering the education level, the study reveals that most respondents were dominated by graduate-level individuals (32.49%). Meanwhile, 137 (31.35%) respondents have a postgraduate education level. This indicates that undergraduate and graduate students have engaged with ChatGPT more than their postgraduate counterparts. Furthermore, the participants were primarily based in Kathmandu 264 (60.41%), while 123 (28.15%) were located in Lalitpur. Only, 11.44% respondents were from Bhaktapur.

Challenges while using ChatGPT and Managerial Solution

In this study, most respondents, i.e., 59.04%, have faced challenges while using, whereas the remaining 40.96% do not face any challenges. 40.27 %(176) of respondents identify accuracy and reliability as the major problem. 24.94% of respondents expressed data privacy and security, while 19.91% expressed concerns about plagiarism. Additionally, 15.79% of respondents mentioned bias and misinformation concerns as a challenge, followed by a lack of adaptability (12.13%), 8.01% user experience, and other challenges (1.6 %). Thus, the top challenges identified are accuracy and reliability, data privacy and security, plagiarism concerns, bias and misinformation.

Respondents were asked about the challenges they faced and, if manageable, their strategies for managing those challenges. This can contribute to better management of user challenges. By analysing the respondents' responses, it was found that out of 403 respondents, the majority, i.e., 248 respondents, agreed that the challenges can be managed, and only ten respondents agreed that challenges cannot be managed.

Figure 2

Challenges

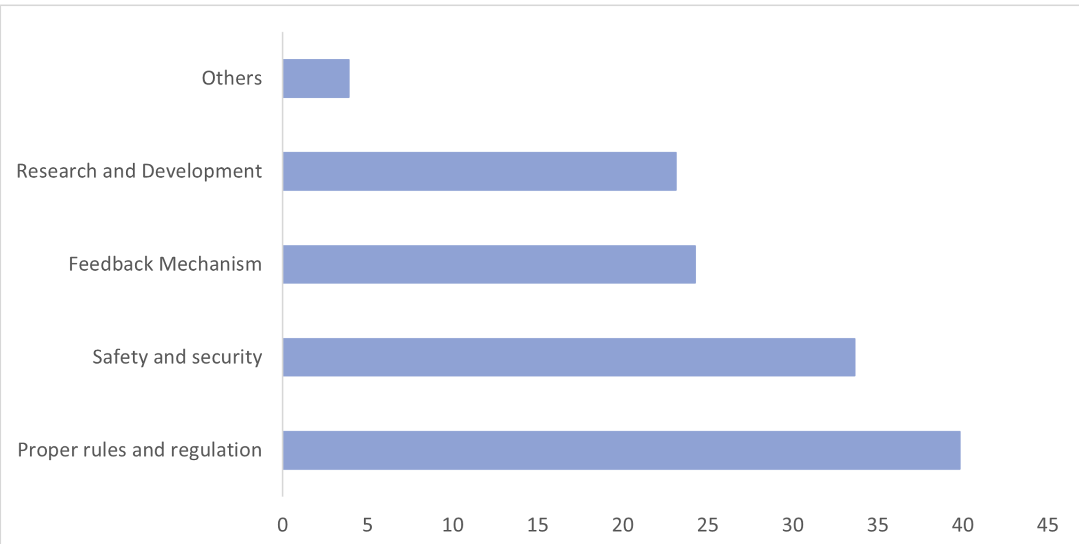


Figure 2 reveals that out of 248 respondents who believe that the challenges can be managed, 39.82% of respondents believed that by implementing proper rules and regulations, problems can be solved. Similarly, 33.64% of respondents suggested focusing on proper safety and security measures. Additionally, 24.26% of respondents advised a feedback mechanism. Research and development are suggested by 23.11% of respondents as a management strategy. Lastly, a small percentage of respondents, 3.89%, suggest exploring other options such as regular updating, improvement in the algorithm, and reliable and updated information.

Inferential Analysis

Common Method Bias: In order to test common method bias, the full collinearity test is performed. Gunarathne et al. (2021) state that Variance Inflation Factor (VIF) values should not exceed 3.3, suggesting that standard bias methods do not influence the data. All the VIF values in Table 3 fall under this criteria, so data are not impacted by common technique bias, and there is no multicollinearity problem.

Table 3

VIF for Common Method Bias- Multicollinearity

	atuc	bi	peu	pu
VIF	1.57	2.334	2.151	2.148

Measurement Model

Under the measurement model, validity and reliability are tested. This study is a reflective measurement model. Internal Consistent Reliability, Convergent Validity and Discriminant Validity are observed in the reflective model.

Internal Consistent Reliability: Two measures are commonly used to assess internal consistency reliability: Cronbach's alpha (CA) and composite reliability (CR). A dataset must fulfil specific requirements in order to show consistent internal reliability. Firstly, Cronbach's Alpha should be greater than 0.6 (Bujang et al., 2018). Additionally, Composite Reliability should have higher values as it indicates a higher level of dependability. For example, a value between 0.60 and 0.70 is considered "acceptable", while values between 0.70 and 0.90 are considered "satisfactory to good". However, extremely high values of 0.90 and above indicate potential redundancy among the items, which can be problematic (Lawaju et al., 2024; Purwanto & Sudargini, 2021). All Cronbach's Alpha (CA) and Composite Reliability (CR) criteria were satisfied in this study. As a result, the model of this study has internal consistency reliability.

Internal Consistent Reliability

Constructs	**Cronbach's alpha**	**Composite reliability**
atuc	0.648	0.666
bi	0.934	0.934
peu	0.839	0.842
pu	0.815	0.82

Convergent Validity: Factor loading and Average Variance Extracted (AVE) are considered to measure the convergent validity. According to the AVE, the value must be at least 0.5. According to Maskey and Nguyen (2018), items with loading values of less than 0.4 should be dropped, and factor loading of 0.7 and above is considered ideal. Some indicators in this study have factor loading below 0.7. As a result, the items corresponding to the construction atuc3 and atuc4 from the attitude towards using ChatGPT were dropped to achieve an AVE of 0.5 or above as their loading values were lowest.

Table 5

Convergent Validity

Construct	Indicators	Outer Loading	Average variance extracted (AVE)
Perceived ease of use	peu1	0.731	0.608
	peu2	0.819	
	peu3	0.774	
	peu4	0.78	
	peu5	0.792	
Perceived usefulness	pu1	0.757	0.577
	pu2	0.751	
	pu3	0.666	
	pu4	0.795	
	pu5	0.82	
Attitude towards to use ChatGPT	atuc1	0.769	0.586
	atuc2	0.701	
	atuc5	0.821	
Behavioural intention	bi1	0.877	0.791
	bi2	0.874	
	bi3	0.884	
	bi4	0.912	
	bi5	0.899	

Discriminant Validity: Fornell and Larker criterion is used to determine the difference between different components in the model and assess discriminant validity. However, solely relying on the Fornell and Lacker criterion is insufficient to test discriminant validity. Therefore, Henseler et al. (2015) recommended the Heterotrait-Monotrait (HTMT) ratio scale and the cross-loading method to examine the discriminant validity.

Initially, the Fornell and Lacker criterion was checked and satisfied, as the square roots of all AVEs were more prominent than the corresponding correlations (Hair et al., 2020).

Table 6

Fornell-lacker Criterion

Constructs	atuc	bi	peu	pu
atuc	0.765			
bi	0.678	0.889		
peu	0.582	0.702	0.78	
pu	0.521	0.688	0.701	0.759

Moving forward, HTMT is being used to verify further discriminant validity based on estimating the correlation between the constructs, as proposed by (Dijkstra and Henseler, 2015). Heterotrait-Monotrait (HTMT) values below 0.85 are widely accepted as demonstrating discriminant validity. Looking at Table 7, it can be observed that all the HTMT ratios are below the threshold value of 0.82, which further confirms the discriminant validity of this study. Table 7

HTMT Results

	atuc	bi	Peu	pu
atuc				
bi	0.859			
peu	0.781	0.792		
pu	0.698	0.786	0.844	

In the cross-loading analysis, the factor loading of each indicator on its assigned construct is expected to be higher than the loading on any other construct (Ab Hamid et al., 2017). The results in Table 8 demonstrate that all items have more significant factor loadings on the underlying constructs to which they belong than on any other construct. Additionally, there is no problem with cross-loading as the cross-loading values of the item are less than 0.7 with other constructs (Hair et al., 2020).

Table 8

Factor cross loading

Items	atuc	bi	peu	pu
atuc1	0.769	0.498	0.428	0.326
atuc2	0.701	0.43	0.402	0.35
atuc5	0.821	0.608	0.499	0.499
bi1	0.602	0.877	0.608	0.611
bi2	0.609	0.874	0.603	0.588
bi3	0.595	0.884	0.664	0.628
bi4	0.604	0.912	0.653	0.623
bi5	0.603	0.899	0.599	0.609
peu1	0.367	0.456	0.731	0.514
peu2	0.493	0.577	0.819	0.574
peu3	0.458	0.585	0.774	0.521
peu4	0.449	0.57	0.78	0.563
peu5	0.492	0.545	0.792	0.556
pu1	0.327	0.477	0.513	0.757

pu2	0.412	0.546	0.505	0.751
pu3	0.406	0.494	0.5	0.666
pu4	0.352	0.507	0.512	0.795
pu5	0.464	0.577	0.614	0.82

Goodness of Fit

According to Cangur and Ercan (2015), the standardised root mean square residual (SRMR) is a measure that compares the observed covariance matrix with the model-implied covariance matrix. SRMR represents an acceptable fit when it generates a value less than 0.08 (Basnet et al., 2024). This study's SRMR value is 0.060, above the required threshold value and approving goodness of fit (GoF).

Structural Model

Structural modelling performs a bootstrapping analysis to determine the path coefficients and R^2 values. The analysis used a two-tailed test with subsamples of 10,000 and a significance level of 0.05. The PLS 4.0 software connects the observed variables and illustrates the proposed relationships in the conceptual model.

Hair et al. (2011) suggested an R^2 value of at least 0.20 to ensure a satisfactory model fit. Accordingly, the endogenous variable "attitude towards use of ChatGPT" has an R^2 value of 0.361. Similarly, "perceived usefulness" has an R^2 value of 0.49, and "behavioural intention" has an R^2 value of 0.647. All R^2 values exceeded the recommended threshold score. Likewise, The VIF calculation displayed that all values are less than 5 (Table 12), indicating a satisfactory collinearity status, as Hair et al. (2011) suggested that the VIF value should be less than 5 to ensure a satisfactory collinearity status.

Table 9

Coefficient of Determination (R2) and VIF

Endogenous Latent Factors	VIF	R^2
Atuc	1.573	0.361
Peu	2.249	
Pu	2.039	0.490
Bi		0.647

Path Coefficient

In the end, a bootstrapping was done in Smart PLS4 to determine the path coefficient and its associated t-value for direct and mediating relationships. This study has six hypotheses. Path analysis is run with the help of Smart PLS Software, and the calculation and interpretation are based on the results gathered from the Smart PLS4. On the Smart PLS4 screen, the observed variables were linked to other variables, representing the hypothesised linkage in the conceptual model. The resulting path model and path analysis results are usually displayed as a path diagram.

Figure 3

Path Coefficient

Hypothesis Test

There are seven hypotheses in this study, of which are supported. Smart PLS is used to run path analysis, and the results are used to calculate and interpret the data. The result is supported at significance level ***P<0.05 and when the beta value lies within the confidence interval. All the results of the hypothesis are shown in Tables 13 and 14, which give an overview of the findings. The empirical data support hypotheses H1, H2, H3, H4, H5, H6, and H7 are supported as the beta coefficient of the respective hypothesis lies within the lower limit. The upper limit confidence interval illustrates that the P-value is less than 0.05 for all hypotheses, meaning there is a significant relationship between all the variables.

Table 10

Hypothesis Testing

Hypothesis		Beta (β)	SD	T-value	P-values LL 2.5%	CI UL 97.5%		Decision
H1	atuc -> bi	0.678	0.034	19.914	0	0.602	0.737	Supported
H2	peu -> atuc	0.427	0.071	5.984	0	0.281	0.56	Supported
H3	peu -> pu	0.701	0.04	17.672	0	0.612	0.769	Supported
H4	pu -> atuc	0.222	0.071	3.107	0.002	0.08	0.358	Supported

Mediation Analysis

The mediation hypothesis is tested by bootstrapping the indirect effect. The proposed mediations are checked and analysed with condition p-values>0.05, and the original sample (beta) falls in the range of Confidence Interval (Kock, 2015). As per Table 14, all mediation paths are satisfied. So it is partial-mediation. The results also give data about the specific indirect effect to test the mediation effect of Perceived usefulness, Perceived ease of use, attitude towards the use of ChatGPT and Behavioural Intention.

Table 11

Mediation Analysis

Hypothesis		Beta(β)	SD	T-values	P-values	LL 2.5%	UL 97.5%	Decision
H5	peu -> atuc -> bi	0.289	0.052	5.54	0	0.187	0.392	Supported
H6	peu -> pu -> atuc -> bi	0.105	0.037	2.847	0.004	0.038	0.181	Supported
H7	pu -> atuc -> bi	0.15	0.051	2.972	0.003	0.053	0.25	Supported

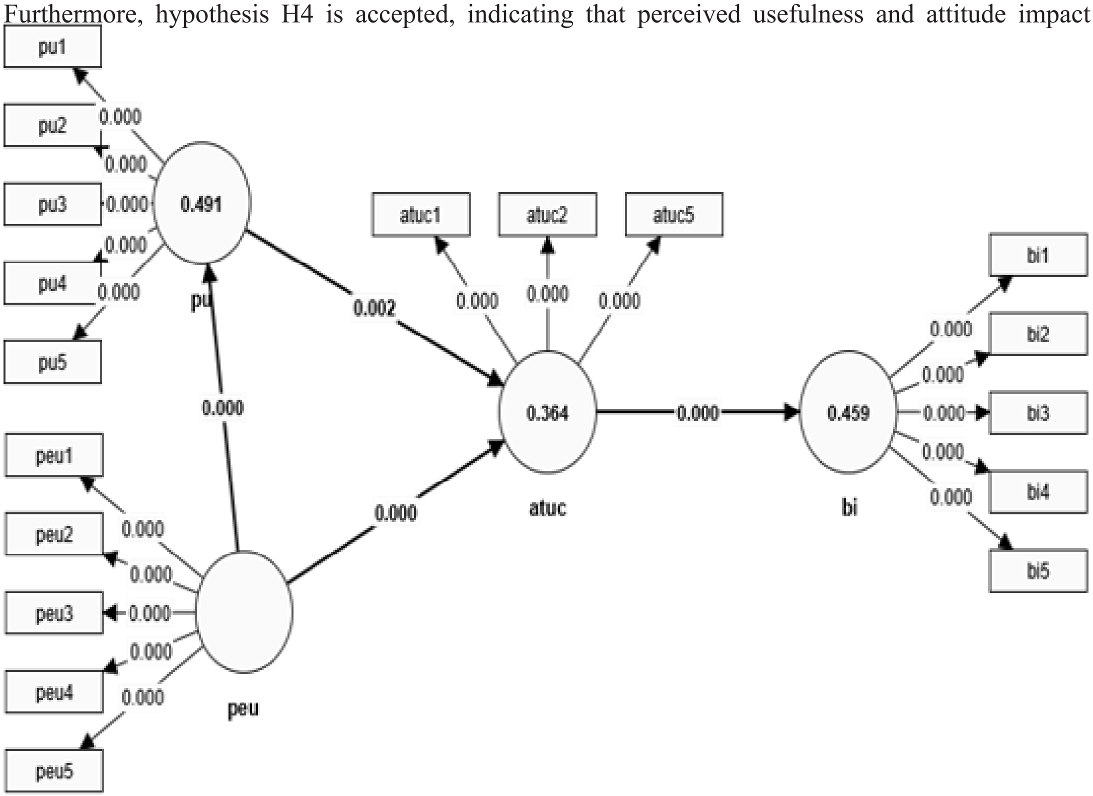
5. Discussion

This research tries to analyse the impact of ChatGPT on Management Education. Various variables are used to analyse behavioural intention. Such factors are perceived ease of use, perceived usefulness, and attitude. In order to develop a link between the constructs, SEM is used. Measurement and structural analysis are done for this. Several hypotheses were developed as per the conceptual framework. Hypothesis 1, 2, 3 and 4 are accepted as their p values are below 0.05, meaning there is a relationship between the variables.

H1 test the relationship between attitude and behavioural intention, respectively. H1 is supported, indicating that attitude has a significant relationship with behavioural intention, indicating that individuals' attitudes strongly influence their behaviour. This result contradicts the study by Tan (2013) as it suggests that attitude toward green and sustainable homes had a positive causal effect on behaviour. The findings of the study support Hypothesis 2, which proposed a significant relationship between perceived ease of use and attitude towards the use of ChatGPT. This means that the attitude to ChatGPT is significantly influenced by perceived ease of use. In Saudia Arabia, perceived ease of use has a considerable marginal impact on adopting digital banking (Alnemer, 2022).

Similarly, looking at the relationship between perceived ease of use and usefulness supports H3. Perceived Ease of Use can influence perceived usefulness positively and significantly. According to the TAM, if people believe that information technology can be used positively, they are more likely to embrace and use it more frequently. One of the main factors influencing how the system is used and how users perceive its ease of use and utility is Bertangnolli (2011). Comparing the perceptions of usefulness to other variables like attitudes, satisfaction, and other perceptual measures, they were more robust and consistent with the acceptance of information technology (Machdar, 2019).

Furthermore, hypothesis H4 is accepted, indicating that perceived usefulness and attitude impact



behavioural intention. Y. L. Chen et al.(2015) also stated that attitudes toward the use of online ordering platforms from securities brokers could be favourably impacted by perceived usefulness is significant Moreover, empirical evidence has been presented (Sentosa, 2012) demonstrating that a perceived utility significantly and favourably impacts attitudes regarding the use of information technology or related systems.

Three mediating hypotheses have been generated, and mediation analysis has been conducted. Hypothesis 5, 6 and 7 are also accepted, indicating that attitude mediates the relationship between perceived ease of use and behavioural intention. Perceived usefulness significantly impacts perceived ease of use, attitude and behavioural intention. This result aligns with the study by Cheng and Chen (2011). This means that perceived ease of use (PEU) influences people's attitudes toward online learning. PEU measures user opinions and ease of use of online learning (Zahir Osman et al., 2012).

6. Conclusion

This study aims to deepen the impacts of ChatGPT in Management Education. It also investigates general understanding factors affecting behavioural intention. In addition, it identified user challenges and proposed strategies to overcome them.

The first specific objective of this study is to identify the factors affecting students' behavioural intention. Factors such as perceived ease of use, usefulness, and attitude affect behavioural intention. The study also shows that perceived ease of use does not directly impact behavioural intention. Additionally, perceived usefulness has a significant impact on behavioural intention. It is found that attitude mediates the relationship between perceived ease of use, perceived usefulness and behavioural intention. The significant challenges faced by the students are accuracy and reliability, data privacy and security, plagiarism concerns, bias and misinformation. Finally, the last objective is to recommend managerial solutions for reducing the challenges. The central managerial solutions for reducing the challenges are proper rules and regulations, safety and security measures, feedback mechanisms, research and development, regular updating, algorithm improvement, and reliable and updated information. Here, perceived ease of use and perceived usefulness influenced behavioural intention. The study also highlighted the impact of attitude towards using ChatGPT on perceived ease of use, usefulness, and behavioural intention.

7. Implication of the Study

Artificial intelligence (AI) has the potential to drive innovation and improvement in education in several ways, such as by providing personalised and engaging learning experiences for students, improving the efficiency of teaching and learning, and supporting research and development in education. The findings suggest that ChatGPT contributes to increased access to educational information. The finding shows how ChatGPT can be used in education. It gives ideas to teachers and researchers. Universities need help from the government and policymakers. The government can invest in new technology and support special centres for education and AI. This support can motivate people to use these tools. Schools can also collaborate with AI companies to control how much students use AI. Moreover, this study will be helpful to the Ministry of Communication and Information to understand people's concerns about using AI in education. Policymakers should create rules to handle privacy and security issues with AI.

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