AI in the Classroom: Analysing ChatGPT Usage Among School and College Students

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ABSTRACT

This study explores the usage of ChatGPT among school and college students through the lens of the Unified Theory of Acceptance and Use of Technology (UTAUT) model, with an emphasis on age group as an additional moderating factor. A total sample of 396 students was collected through structured questionnaires. The UTAUT model's key constructs are Performance expectancy, Effort expectancy, social influence, and Facilitating conditions these were examined to determine their impact on students' behavioural intention to use ChatGPT. Age was included as a moderating variable to assess on the relationship between these constructs and intention to use ChatGPT. The study highlights the importance of age in understanding technology adoption among students, providing valuable insights for educators and policymakers aiming to integrate AI-driven tools like ChatGPT into educational settings effectively.

Key-words: *School and College Students, ChatGPT, UTAUT model*

. INTRODUCTION

The rapid advancements in natural language processing technologies, exemplified by the emergence of ChatGPT, have garnered significant attention from the educational community. This literature review aims to synthesize the current understanding of how school and college students are utilizing ChatGPT, with the Unified Theory of Acceptance and Use of Technology as a guiding framework.

Recent studies have explored the perspectives of both high school and university students on the adoption and integration of ChatGPT in their academic endeavours [1, 3]. High school students have been found to utilize ChatGPT for a variety of purposes, including academic support, social communication, and personal management, across both educational and social contexts [1]. Furthermore, these students have expressed a positive outlook on the potential of ChatGPT to significantly impact their lives in the coming years [1].

At the university level, research has delved into the determinants of students' acceptance and adoption of ChatGPT as a tool for translation tasks [3]. Applying the UTAUT model, the study identified key factors that influence students' intention to use ChatGPT, such as performance expectancy, effort expectancy, and social influence, as well as the moderating effects of use experience and translation training [3].

While the potential benefits of ChatGPT in education have been discussed, researchers have also explored the challenges and implications of its use. Halaweh [2] has addressed educators' concerns about the integration of ChatGPT into educational contexts, emphasizing the need for careful implementation and guidance. Additionally, Zhai [2] has recommended modifying instructional objectives to focus more on students' creativity and critical thinking, rather than relying solely on ChatGPT's capabilities.

As the adoption of ChatGPT continues to evolve, there is a growing need to understand the factors that shape students' acceptance and utilization of this technology. The UTAUT model provides a valuable framework for investigating the complex interplay of performance expectancy, effort expectancy, social influence, and facilitating conditions that influence students' decisions to engage with ChatGPT [3].

Overall, the literature highlights the multifaceted nature of ChatGPT's integration into educational settings, with both opportunities and challenges emerging. Educators and policymakers must carefully navigate this evolving landscape, ensuring that the benefits of ChatGPT are harnessed while addressing the potential pitfalls and maintaining a focus on students' holistic development.

Literature Review

The current study employs Venkatesh et al.'s [7] UTAUT model as the foundational theoretical framework. The Unified Theory of Acceptance and Use of Technology (UTAUT), introduced by Venkatesh along with Morris, Davis, and Davis in 2003, serves to elucidate and forecast the factors that affect users' acceptance and utilization of technology. This integration leads to the formation of four essential constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions [7]. Together, these constructs offer a robust framework for comprehending technology adoption and use [8]. The UTAUT model has been extensively applied in both research and practice to guide the design and implementation of technological interventions. Specifically, the UTAUT framework can be tailored to explore users' acceptance and utilization of AI tools [9]. When considering AI technology, the UTAUT constructs can be adjusted to capture the unique characteristics and capabilities of AI [11,10].

Performance expectancy: Within the UTAUT model, performance expectancy is a significant concept which describes and predicts an individual's behaviour towards technology acceptance. It communicates that the use of a specific technology will increase process efficiency and effectiveness [7]. Important work in the area of chatbots shows that perceived usefulness is fundamental to user acceptance and engagement [5]. For ChatGPT, it involves the users' anticipations of its ability to augment their performance in tasks they perform arising from factors such as perceived usefulness and fit with existing routines.

Effort expectancy refers to the degree of ease that people perceive using a technology [7]. This perception has formed according to prior experience, technical skills, technology complexity and available resources [6] (Refer Fig 1). The more effort a technology is perceived to require, the less likely it will be adopted [12]. In the case of ChatGPT, high effort expectancy will most likely enhance its adoption as by itself ease-of-use is a motive to include into daily routines.

Social influence reflects the perceived expectations of an individual from important others towards the use technology [7]. Social influence can have a positive impact on both perceived usefulness and ease of use, facilitating adoption [13– 14] or it may generate scepticism towards the innovation with its attendant resistance [15]. A review of social influencers including friends, family members, associates and online reviews [16] With ChatGPT, appealing to positive social influence factors can enhance adoption while reliability and reputational issues create resistance. There is evidence such as rapid uptake of ChatGPT after its release [17,18] to suggest the importance of this process.

Facilitating conditions includes the perception that adequate organizational and technical supports are in place for technology use [7]. This includes use of equipment, software and support provided [19]. Adoptability also needs to align with facilitating conditions, including reliable internet access and technical support for ChatGPT. The availability of these resources is conducive to being used, while it lacks can be an obstacle for them becoming part of everyday life.

Behavioural intention to adopt ChatGPT is the degree of an individual who desires and ready to use it in certain tasks such as academic support, research [20,21,22,23]. This is a fundamental concept pertaining to technology adoption in the UTAUT framework.

Age as a moderating factor in the relationship between user perception and intention to use ChatGPT, as different age groups may exhibit varying levels of technological adoption and familiarity, which can influence their willingness to engage with AI-based tools. For instance, younger users, who are generally more tech-savvy, may have a higher intention to use ChatGPT compared to older users.[7]

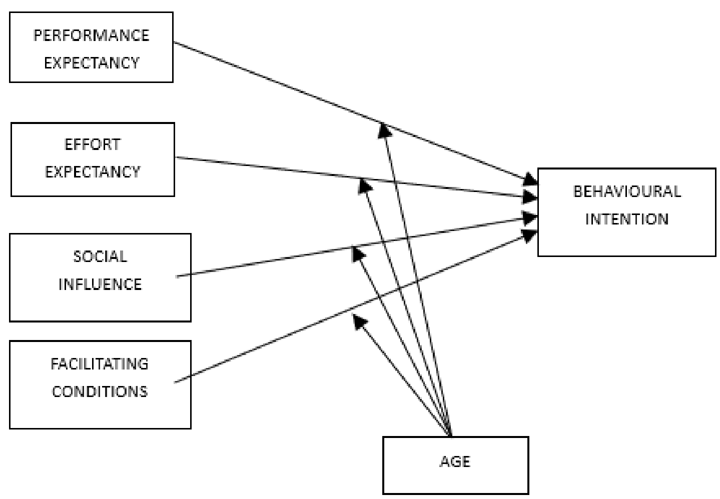


Fig: The conceptual framework

Research Methodology

The research model described in [28] utilized a method involving a survey questionnaire, for data collection. The aim was to validate the model, test hypotheses meet study objectives and assess the impact of the constructs being investigated. The questionnaire consisted of 35 items tailored to the study objectives. The first part collected details from respondents, such as gender, age, academic year and institution name. The following section focused on constructs like Performance Expectancy, Effort Expectancy, Social Influences Facilitating Conditions and age in relation to Behavioural Intention.

A cross-sectional survey approach was employed to gather data and explore relationships between dependent variables. The survey used a five-point Likert scale ranging from disagree (1) to strongly agree (5) to gather insights from participants [24]. Data collection was done via Google Forms distributed through email and WhatsApp channels. This method ensured all responses were captured without missing data or outliers [25]. Data analysis was carried out using SPSS and SmartPLS4. Advanced statistical tools, for data analysis [26,27].

The researchers used the equation model (Measurement Assessment Model) to analyse the data and figure out the sample size.

Hypothesis Framing:

H1: Performance Expectancy positively affects the behaviour intention of ChatGPT usage

H2: Effort Expectancy positively affects the behaviour intention of ChatGPT usage.

H3: Social Influence positively affects the behaviour intention of ChatGPT usage.

H4: Facilitating Condition positively affects the behaviour intention of ChatGPT usage.

H5: Age moderate the relationship between independent variable and behavioural intention of ChatGPT usage.

H5A: Age moderates the relationship between Performance expectancy and behavioural intention of ChatGPT.

H5B: Age moderates the relationship between Effort expectancy and behavioural intention of ChatGPT.

H5C: Age moderates the relationship between Social influence and behavioural intention of ChatGPT.

H5D: Age moderates the relationship between Facilitating conditions and behavioural intention of ChatGPT.

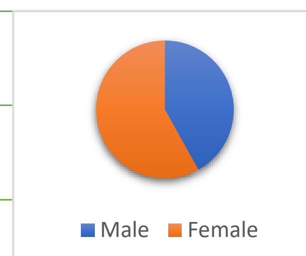
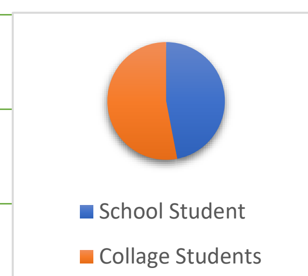
Objectives of the research study

- To examine the factors affecting the students' behaviour to use ChatGPT.
- To explore age as a moderator in understanding the use of ChatGPT among school and college students.

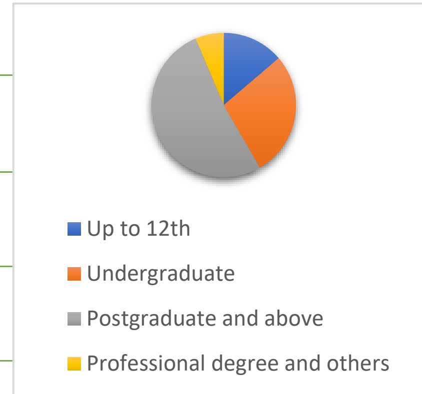
Pilot Analysis

A pilot study involving a sample of 52 users from the Delhi-NCR region revealed that two out of 30 items had outer loading values below the threshold of 0.70. These items did not satisfy the reliability and validity criteria and were consequently excluded from further analysis. As a result, the study proceeded with 14 items, excluding BI2 and FC3.

Respondent Demographic Analysis

DEMOGRAPHIC	FREQUENCY	PERCENTAGE	
Gender			
Male	166	41.91	
Female	230	58.08	
Age			
School students	186	46.96	
Collage students	210	53.03	

Level of Education			
Up to 12th	57	13.63	
Undergraduate	110	27.7	
Postgraduates and above	204	51.51	
Professional degree & Others	25	6.31	



The demographic analysis of the respondents reveals that out of a total sample size of 396 individuals, a majority are female, accounting for 58.08% (230 respondents), while males constitute 41.91% (166 respondents). When considering age, the sample is almost evenly split between school students, who make up 46.96% (186 respondents), and college students, who represent 53.03% (210 respondents). In terms of educational level, most respondents have completed postgraduate studies, making up 51.51% (204 respondents). This is followed by 27.7% (110 respondents) who are undergraduates, 13.63% (57 respondents) with education up to the 12th grade, and 6.31% (25 respondents) who fall into other educational categories.

Measurment Model Analysis

SmartPLS is specifically designed for Partial Least Squares Structural Equation Modelling (PLS-SEM), making it particularly suited for analysing complex models involving latent variables, as noted by Ramayah et al. (2018). In this study, PLS-SEM was employed to examine the structural model and conduct measurement analysis. The measurement model, also known as the outer model, represents the relationships between indicators, while the structural model describes the connections between latent variables. Hubona (2009) highlighted that the maximum likelihood method was used to evaluate the proposed research model using PLS-SEM. To assess reliability and convergent validity, several metrics were employed, including factor loadings, composite reliability (CR), and average variance extracted (AVE). A higher factor loading indicates the dimensionality of the factors. The CR metric is a reliable tool for assessing reliability, providing accurate values through factor loadings within the derived formula. AVE represents the average amount of variance captured by a particular variable that defines a latent construct. When discriminant validity is achieved across factors, AVE serves as a measure to assess the convergence of each factor. As shown in Table 1, the data instrument used in this study meets the required criteria for reliability and convergent validity. Table 2 provides a detailed evaluation of the instrument's validity and reliability, presenting the results for each factor based on the variables obtained from the data instrument.

Table 2: Reliability and Validity- Output of Confirmatory factor analysis (CFA)

CONSTRUCT	**INDICATOR**	**LOADING**	**CRONBACH'S ALPHA**
PERFORMACE EXPECTANCY	PE1 PE2	0.754 0.798	0.751

	PE3	0.857	
EFFORT EXPECTANCY	EE1 EE2 EE3	0.775 0.724 0.835	0.765
SOCIAL INFLUENCE	SI1 SI2 SI3	0.802 0.855 0.844	0.793
FACILITATING CONDITION	FC1 FC2	0.929 0.948	0.881
BEHAVIOURAL INTENTION	BI1 BI3	0.853 0.845	0.612

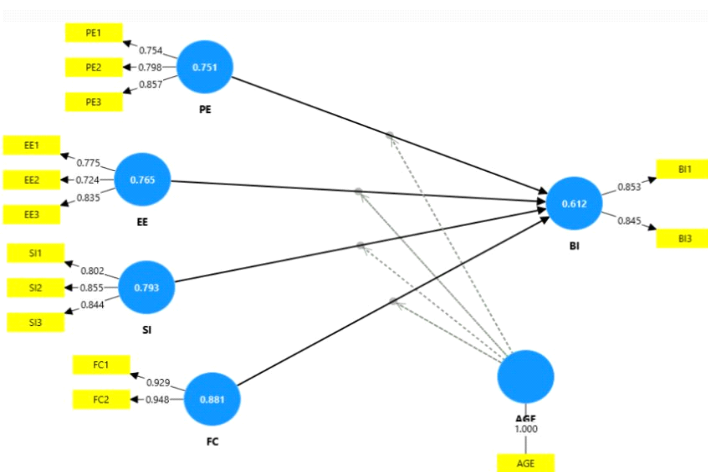


Figure 2: The Measurement Model - Latent construct's outer loading values

The figure represents a structural model analyzing the relationships between key latent constructs, likely using Partial Least Squares Structural Equation Modeling (PLS-SEM). The constructs include Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Behavioral Intention (BI), and the moderating effect of Age x FC. Each construct is represented by blue circles, with corresponding indicator variables (e.g., PE1, EE1) shown in yellow. The outer loadings of indicators on their respective constructs are shown, all exceeding the recommended threshold of 0.7, indicating strong indicator reliability. The structural paths between constructs are marked by solid arrows, reflecting hypothesized relationships, with the path coefficients annotated along each connection. Dashed lines indicate non-significant relationships. The moderating variable (Age x FC) and the direct relationship between age and BI are included, highlighting interaction effects. Overall, the model depicts how various predictors and moderating factors influence behavioral intention (BI) within the study context.

Assessment of Structural Model

For assessment of the structural model, the study has applied R square measure, which is most commonly used for structural model assessment. It measures the explained variance of all latent variables to its total variance. There is one endogenous variable in the model, the R2 value of BI being 0.758. Hence, the endogenous variables are explaining variance above 0.67, the model is explaining substantial variance by its latent variables.

Table 3: To evaluate R2 (R-square) and f2 (f-square)

CONSTRUCTS	F-SQUARE	R-SQUARE	R-SQUARE ADJUSTED
Performance expectancy	0.030	0.0686	0.679
Effort expectancy	0.049		
Social Influence	0.063		
Facilitating conditions	0.002		

f2 effect size assesses the influence of particular exogenous latent type variable upon an endogenous type of variable (Giao and Vuong, 2019). Evaluating the effect size of every path is another approach towards structural model analysis (Cohen, 1988). Effect size measures if there was significant impact of an independent latent variable upon a dependent type of variable. In the structural model, f sq. values of 0.02, 0.35, 0.15 and suggest a small, large, medium effect of an exogenous variable on the endogenous variable (Chin, 1998).

Table 4: Results of hypothesis testing and structural relationships

Hypothesis relationship	T statistics	P values	Hypothesis No.	Result
PE-> BI	4.256	0.000	H1	
EE->BI	3.572	0.000	H2	
SI->BI	5.087	0.301	H3	
FC->BI	1.035	0.000	H4	

The result showed that the social influence, performance expectancy, Hedonic motivation, effort expectancy, plays a significant role in determining behavioural intention on the usage of ChatGPT. Facilitating condition and habit have shown insignificant effect on intention of using ChatGPT.

GAP

There is a lack of data on the use of AI tools, such as ChatGPT, among college and high school students, despite their increasing integration in educational contexts. Studies that have already been done mostly concentrate on ChatGPT's technological features or any possible ethical implications. But little thought has gone into figuring out how school and college students actually utilize this tool for homework, research, and learning, or how it affects their creativity, critical thinking, and academic success. Furthermore, a thorough examination of the hazards is lacking, such as the possibility of an excessive reliance on AI for tasks, which could have long-term consequences for students' academic performance. Developing fair criteria for incorporating AI in education requires addressing these discrepancies.

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Moderation analysis

Hypothesis testing

Table 5: Result of SEM - Hypothesis testing

Relationship	Hypothesis No.	T statistics	P value	Result
EE -> BI	H2	3.572	0.000	
FC -> BI	H4	1.035	0.000	
PE -> BI	H1	4.256	0.000	
SI -> BI	H3	5.087	0.000	
AGE x EE -> BI	H5B	1.671	0.078	
AGE x SI -> BI	H5C	0.358	0.721	
AGE x FC -> BI	H5D	0.787	0.431	
AGE x PE -> BI	H5A	3.625	0.000	

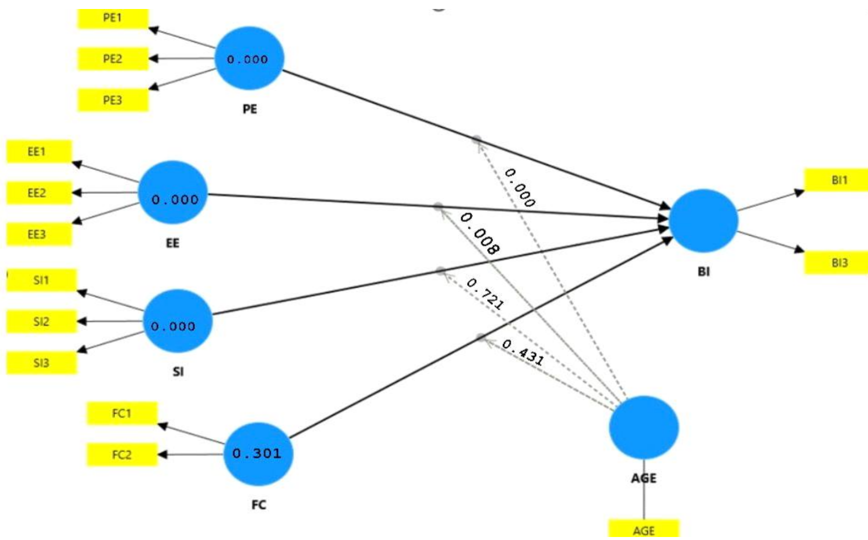

Fig: Model with P values.

Slope Analysis

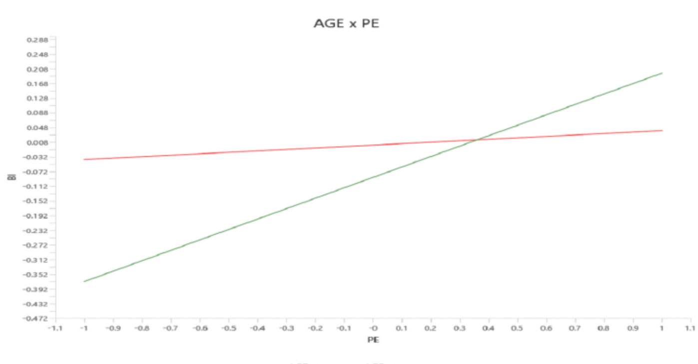

Figure 3: Slope analysis- AGE x PE->BI

The findings are also clear from the above slope analysis that school students feels that usage of ChatGPT is very useful and it helps in extending their behavioural intention. On the contrary, the above graph reflects intention to use ChatGPT does not increases with increase in Performance expectancy in case of college students.

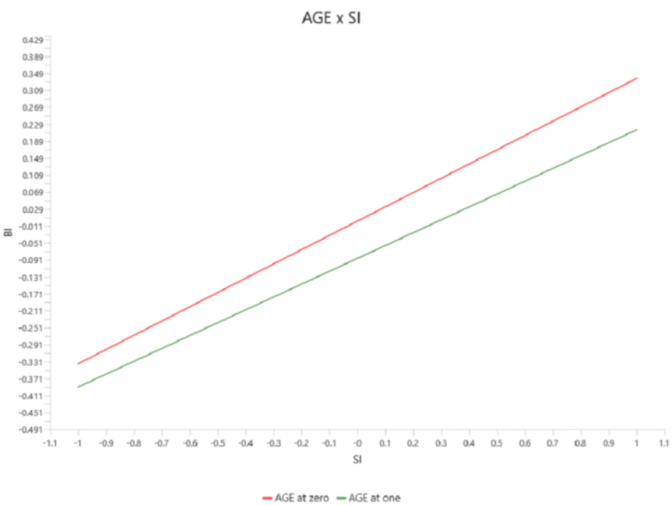

Figure 4: Slope analysis- AGE x SI->BI

The findings are also clear from the above slope analysis that school students' social factor is high, they perceive near one's usage of ChatGPT as important and try to follow. College students being more educated and mostly working professionals, make their own decision.

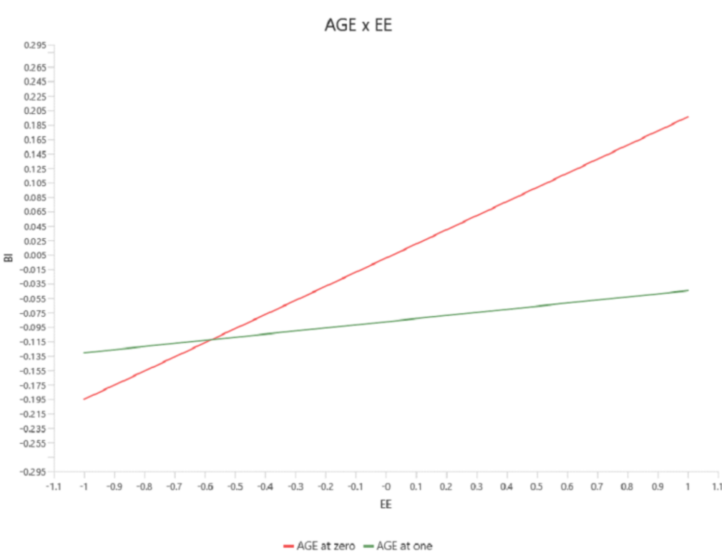

Figure 5: Slope analysis- AGE x EE -> BI

The findings are also clear from the above slope analysis that college students feel that their effort is reduced and their intention to use ChatGPT increases whereas school students feel more apps need to be considered. They need many factors and applications available at the time of using of ChatGPT which becomes a tedious task and, hence requires more effort.

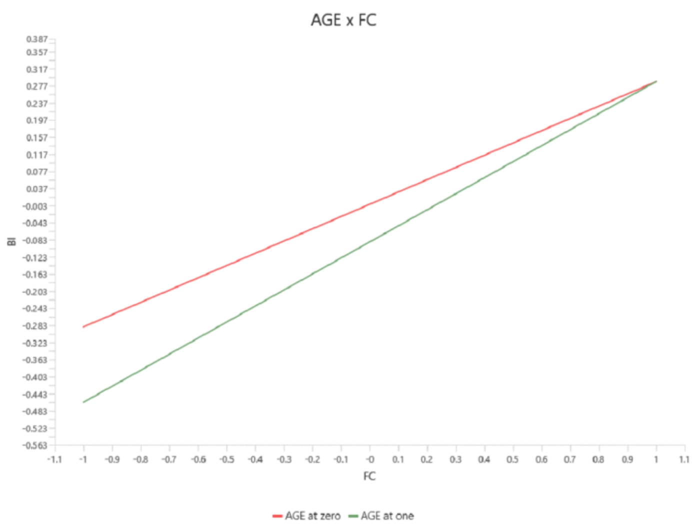

Figure 6: Slope analysis- AGE x FC -> BI

The findings are also clear from the above slope analysis that all age groups are showing trend line in almost similar direction which shows that with increase in facilitating condition, means support of technology on mobile, laptop and their intention to use ChatGPT.

FINDINGS AND DISCUSSION

The table provides a comprehensive overview of the constructs, indicators, and psychometric properties in a research study focusing on factors influencing the intention to use ChatGPT from school and college students' point of view. The research model has extended UTUAT constructs with age as an individual determinant. Each construct, including Effort Expectancy (EE), Performance Expectancy (PE), Social Influence (SI), Facilitating Conditions (FC), Age(A) and Behavioural Intention (BI), is assessed through multiple indicators. Factor loading for each indicator indicates a strong relationship with their connected constructs, where the values range from 0.614 to 0.905 for BI2 and EE3 respectively. The internal consistency of each construct is measured by their Cronbach's alpha value, with the values ranging from 0.736 to 0.930, indicating good to excellent reliability. Thereafter structural modelling is done, and hypothesis results are discussed indicated the significance role of performance expectancy, social influence, effort expectancy. Moderation analysis through hypothesis testing and slope analysis shown that age moderates the relationship between performance expectancy, effort expectancy, social influence, and the behavioural intention to use ChatGPT respectively. Overall, the study demonstrates strong psychometric properties, indicating that the research model effectively captures the intended constructs related to usage of ChatGPT.

MANAGERIAL IMPLICATION

The research study offers meaningful and valuable insights into the factors influencing students' intention to use ChatGPT in school and college settings. The findings can be utilized by educational institutions and developers to design new strategies that engage a broader student audience and enhance adoption. The novel integrated research model developed in this study contributes to the existing knowledge base while narrowing the research gap in understanding the factors that impact the acceptance and usage rate of ChatGPT among students in educational contexts.

Conclusion

The current research employs a modified UTAUT model to assess key predictors influencing the adoption of ChatGPT in academic settings within the Delhi NCR. This study examines factors that significantly impact individuals' intentions to adopt ChatGPT in educational institutions. Data were collected via a survey method to achieve quantitative results. The participants were learners from leading institutions in New Delhi, India, who are currently engaged in academic studies. Structural Equation Modelling (SEM) was utilized to test the research model's predicted stimulants for their effectiveness in forecasting study outcomes. Key factors such as Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC), along with variables like ChatGPT mindset and age, were identified as influential in shaping behavioural intentions toward the effective adoption and use of ChatGPT in education. This adaptation of the UTAUT model specifically for ChatGPT has demonstrated statistically significant predictors that influence learners' attitudes and intentions toward adopting and utilizing this innovative tool in top Indian institutions.

The primary aim of this research is to explore the factors that shape Indian learners' perceptions and concerns regarding the adoption of ChatGPT and to predict how this innovative technology might benefit their academic pursuits. The behavioural intentions concerning ChatGPT adoption and usage in India can be examined using the research model and proposed hypotheses, making this approach well-suited for achieving the study's objectives. The hypotheses were tested using Structural Equation Modelling (PLS-SEM), with performance analysis employed to assess the structural model, including R-squared values, structural pathways, and t-statistics.

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