# *Analyzing the factors influencing the adoption of Artificial Intelligence(AI) based ChatGPT among youth in Delhi-NCR*

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***Abstract* -** This study examines the adoption and usage of ChatGPT among youth using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework by incorporating additional factor namely information quality, which are particularly relevant to younger generations.

The research investigates how effort expectancy, performance expectancy, habit, social influence, hedonic motivation, and information quality influence the behavioral intention to use ChatGPT. Data was collected from a diverse sample of 504 students (school and college) through collecting responses with the help of google form questionnaire. Hedonic motivation and social influence significantly impact the usage intention among both cohorts, highlighting their preference for engaging and socially endorsed technologies. Intention to use and Habit play crucial roles, with youth valuing ChatGPT's efficiency and ease of access. This study contributes to understanding the technological adoption behavior of younger generations and provides insights for developers aiming to enhance user engagement with AI-driven applications.

***Keywords* - *UTAUT2, ChatGPT, Student intention to use, Information quality.***

## I. INTRODUCTION

Towards the end of November 2022, the launch of the Generative Pretrained Transformer (GPT) caused a significant stir. OpenAI CEO Sam Altman reported that within a week, over a million users had signed up to use GPT-3.5, which is predicated on a large language model (LLM) extensively trained on digital data. To produce language that closely mimics human- generated text, LLM GPT is trained on 175 billion parameters. The foundation of GPT is a pre-trained language model that can comprehend human queries quickly and provide input text that seems real (Gilson, 2023), (Borji, 2023), (Tajik, 2024). ChatGPT, a dialogue-based artificial intelligence tool, can produce responses to prompts that resemble those of a human. Some of the main uses for GPT include language translation, text summarization, content creation, code development, answering queries, and writing plays, essays, and stories (Borji, 2023), (William, 2023), (Tate et al., 2023). Many academic fields, including computer science (Qin et al., 2023), education (Tajik, 2024)(Pardos & Bhandari, 2023), medical (Gilson et al., 2023)(Cascella et al., 2023), cognitive science (Mahowald et al., 2023), and MBA (Mollick, 2023)(Terwiesch, 2023), have shown great interest in GPT.

 

In 1962, Vygotsky postulated that human cognitive development can be attributed to two primary concepts: spontaneous and scientific (Vygotsky, 1962). The proximal learning zone, that highlights the disparity between what learners can accomplish with the support (scientific conception) and what they can do independently (spontaneous conception), was designed to bridge the gap between these spontaneous and scientific understandings (Vygotsky, 1962). By conversing back and forth with GPT, learners can co-create meaning and gain a deeper comprehension of the subject, bridging the gap between GPT's accurate and erroneous responses. The greatest obstacle for learners is the illusion of explanatory, which is the idea that they comprehend a subject matter completely but, in reality, only have an insufficient understanding of it (Tajik, 2024).

Although individuals can benefit from ChatGPT, they need guidance to fully understand a subject by applying logic and evaluating results. GPT can analyze candidates' writing samples, reference letters, and statements of purpose, aiding in screening and selecting qualified applicants to help admissions committees make better decisions and arrange interviews efficiently. Given the variety of accessible machine translation systems, it is unclear how willing individuals are to use ChatGPT for translation and what influences their choice. Additionally, there is insufficient research on the moderating factors affecting the acceptance of ChatGPT for translation. Building on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), this research examines the factors affecting individuals' intention to use ChatGPT as a translation tool. Developed by Venkatesh, Thong, and Xu in (2012), the Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2) builds upon the original UTAUT model to offer a more comprehensive explanation of user acceptance and technology usage behavior. UTAUT 2 adds constructs like Hedonic Motivation, Price Value, and Habit, which enhance the original model's explanatory power. UTAUT 2 is crucial for providing a comprehensive framework to understand the factors influencing technology adoption, especially in consumer contexts. UTAUT 2 is crucial for providing a comprehensive framework to understand the factors influencing technology adoption, especially in consumer contexts. By incorporating additional behavioural determinants, it offers a deeper insight into the motivations behind technology use, making it a valuable tool for researchers and practitioners to develop strategies that enhance user engagement and satisfaction with technological innovations.

The importance of information quality in ChatGPT's use by youth stems from their heavy reliance on digital platforms for acquiring information, communication, and making decisions. Reliable and current information—marked by accuracy, timeliness, completeness, and relevance—is crucial for helping users make well-informed choices. These generations are used to swift information exchange and demand immediate access to trustworthy data. If the information quality is poor, it can lead to misinformation, reduced trust, and dissatisfaction with the platform. Thus, maintaining high information quality is essential to enhance user satisfaction, build trust, and ensure these tech-savvy generations continue to see the value in using ChatGPT. Drawing on the UTAUT2, Venkatesh et al., 2012, this study also explores the factors influencing students' intention to use ChatGPT on Information quality. It also examines the mediating impact of intention to use between independent factors and actual use of use. Further, it studies the ChatGPT experience among youth users and investigates if these factors show similar trends for students who translate and those who do not. .

## II. Review of Literature

To examine technology acceptance among students, the study utilizes the Unified Theory of Acceptance and Use of Technology (UTAUT2) as its main theoretical framework. Initially developed and subsequently refined by Venkatesh and colleagues (Dajani, D., and Abu Hegleh. A. S., 2019, Masoomi et al., 2024), UTAUT2 has demonstrated its effectiveness in comprehending technology adoption across different educational settings. UTAUT2 incorporates additional constructs such as hedonic motivation, price value, and habit, alongside the original determinants: performance expectancy, effort expectancy, social influence, and facilitating conditions. These constructs collectively provide a robust mechanism to predict user intentions and behavior towards technology adoption. This model has been widely used in studies examining a range of educational technologies, such as animations (Dajani & Hegleh, 2019), lecture capture systems (Farooq et al., 2017), e-learning platforms (Zacharis & Nikolopoulou, 2022), mobile devices (Zwain, 2019), and learning management systems (Raza et al., 2021), (Zwain, 2019). By applying UTAUT2 in our research, we aim to gain a comprehensive understanding of student engagement and acceptance patterns regarding ChatGPT, thus contributing to the growing body of knowledge in this emerging field.

Performance expectancy is the belief that utilizing the technology will enhance job performance, while effort expectancy is the perception of how easy the technology is to use. Social influence pertains to the perception that significant others think they should adopt the technology. Facilitating Condition (FC) asserts that ChatGPT will fit students' current schedules and be supported by technology and organizational resources, promoting genuine use behavior (Venkatesh et al., 2003). Masoomi et al., (2024) argue that varying FC levels can directly impact behavioral intention in voluntary situations, hedonic motivation, which pertains to the fun or pleasure derived from using the technology; price value, which assesses the cost-benefit ratio of the technology; and habit, which measures the extent to which people tend to perform behavior automatically due to learning. These factors together provide a comprehensive framework for predicting and understanding user intentions and behavior towards new technologies.

Apart from these factors, we have taken one more factor: Information Quality (IQ). In an organization, member satisfaction and information quality are highly correlated. Numerous studies indicate a solid correlation between user satisfaction and information quality. Previous research has also demonstrated the critical role ChatGPT plays in user happiness, closely related to the user interface (Venkatesh, Thong and Xu, 2012), (DeLone, W. H., & McLean, E. R.,2003) (Van Riel et al., 2004). Users may lose faith in ChatGPT if they receive misleading or erroneous information (Van Riel et al., 2004) Therefore, it is important to include this factor too.

This study explores the adoption of ChatGPT among students using the UTAUT2 developed by Venkatesh, Thong and Xu, (2012) integrated with Information Quality (IQ). The research examines the influence of performance expectancy, effort expectancy, social influence, and facilitating conditions on user intentions and usage behavior. Social influence and ease of use significantly impact their acceptance, with GenZ valuing utility and student emphasizing user-friendly interfaces. The study highlights the role of technological facilitation in driving the widespread adoption of ChatGPT among these cohorts. Moreover, facilitating conditions, such as availability of devices and internet access, play a critical role in the seamless integration of ChatGPT into daily routines. The generational differences reveal that while Millennial focus on task-related benefits, Gen Z users are drawn to the interactive and conversational nature of the technology. Both cohorts demonstrate a high level of adaptability to new digital tools, indicating a positive outlook for future AI-driven applications. The study underscores the necessity for developers to consider these factors to enhance user engagement and satisfaction across different age groups.

## III. METHODOLOGY

This study uses a descriptive research and empirical analysis approach. Random sampling is employed to gather information about the online usage of ChatGPT. As per Cochran, 1977, the minimum sample size required for quantitative analysis is 385. A general rule of thumb for sample size is to multiply the number of factors by 25; for 10 factors, this equals 250. A structured questionnaire was created for this study, with a sample of 504 youth users from Delhi-NCR who use ChatGPT. The variables are measured on 5-point Likert scale from strongly disagree to strongly agree. Frequency tables, charts, histograms, and percentages will be used to present and interpret the data. Various statistical tools such as Cronbach's Alpha, regression, structural equation modeling, moderation analysis, R-square, and f-square have been applied to the research data. MS Excel and SMARTPLS 4.0 have been used for analyzing and interpreting the respondent data. Based on research objectives, following hypotheses have been framed :

H1- Performance expectancy has a significant impact on the behavioral intention to use ChatGPT.

H2- Effort expectancy has a significant impact on the behavioral intention to use ChatGPT.

H3- Social Influence has a significant impact on the behavioral intention to use ChatGPT.

H4- Facilitating Conditions has a significant impact on the behavioral intention to use ChatGPT.

H5-Facilitating Conditions has a significant impact on the actual use of ChatGPT.

H6- Price Value has a significant impact on the behavioral intention to use ChatGPT.

H7- Hedonic Motivation has a significant impact on the behavioral intention to use ChatGPT.

H8-Habit has a significant impact on the behavioral intention to use ChatGPT.

H9-Habit has a significant impact on the actual use of ChatGPT.

H10- Information Quality has a significant impact on the behavioral intention to use ChatGPT.

H11-Information Quality has a significant impact on the actual use of ChatGPT.

H12-Intention to use has a significant impact on the actual use of ChatGPT.

H13-Behavioural intention mediates the relationship between Facilitating condition and use of ChatGPT.

H14-Behavioural intention mediates the relationship between Habit and use of ChatGPT.

H15-Behavioural intention mediates the relationship between Information Quality and use of ChatGPT.

## IV. RESULTS & ANALYSIS

A pilot study was carried out with a sample of 58 users from the Delhi-NCR region. During the analysis, it was observed that two of the 30 items had outer loading values below 0.70, which did not satisfy the reliability and validity criteria. As a result, these items were excluded from the study. The final analysis included 28 items, excluding BI2 and FC3.

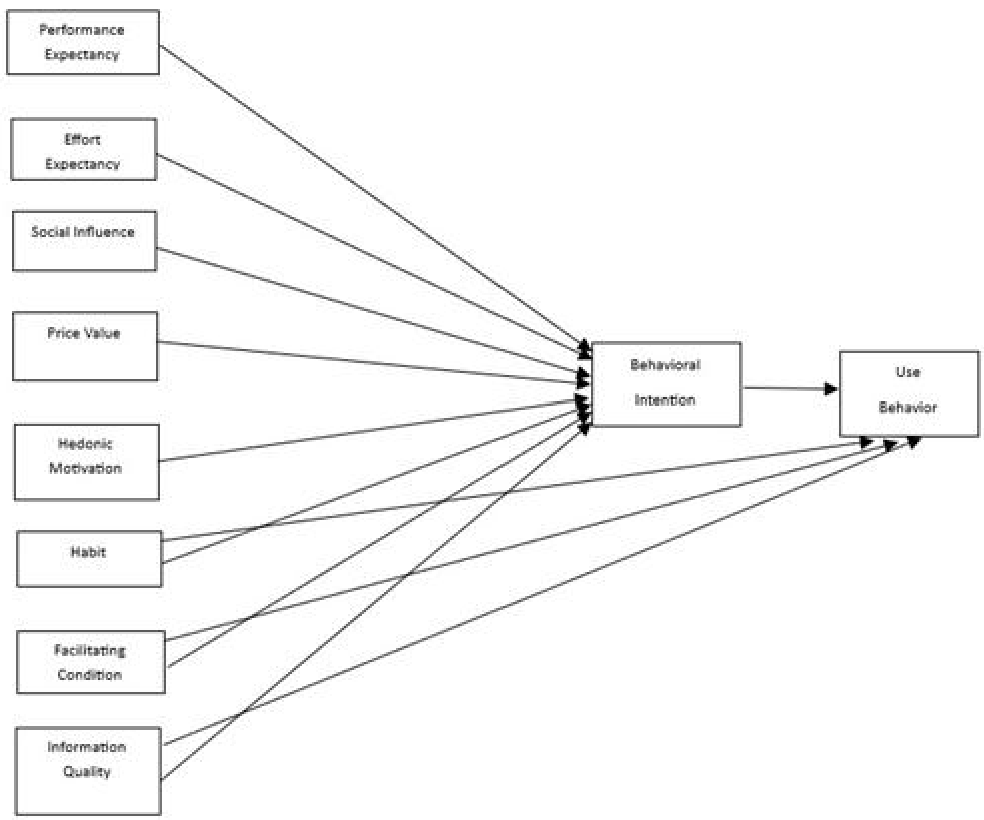


Figure1: The Proposed Conceptual Research Model

The research model includes independent factors such as performance expectancy, social influence, facilitating conditions, effort expectancy, price value, hedonic motivation, habit, and information quality, all of which influences the intention to use ChatGPT and Habit, facilitating condition and Information Quality influences actual usage of ChatGPT.

*TABLE 1: Demographic analysis*

*Source: SPSS 21.0 output*

| **Demographic** | **Frequency** | **Percentage (%)** |
|---|---|---|
| **Gender** | | |
| Male | 298 | 59.12 |
| Female | 206 | 40.87 |
| **Age** | | |
| Millennial | 231 | 45.83 |
| Gen-Z | 273 | 54.16 |
| **Level of Education** | | |
| Upto 12th | 57 | 11.30 |
| Undergraduate | 273 | 54.16 |
| Post Graduate | 124 | 24.6 |
| Others | 50 | 9.92 |

Factor loading of all the latent variable are well above the required threshold limit i.e. 0.700[30] as shown in Figure 2 and also explained in TABLE 2. Reliability of construct is measured through Cronbach's alpha (Giao and Vuong,2019). To assess the internal consistency of a latent variable a minimum score of 0.7 is necessarily required. In this study Cronbach's alpha values of all the latent variables are well above the threshold limit 0.7. Hence, the model shows good internal consistency. Further, average variance is extracted is use to assess convergent validity (Fornell and Larcker, 1981) when AVE is more than 0.5 the convergent validity is confirmed.

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

Source: SmartPLS4 Output

| **Construct** | **Indicator** | **Loading** | **Cronbach Alpha** | **AVE** |
|---|---|---|---|---|
| **Performance Expectancy** | PE1<br>PE2<br>PE3 | 0.761<br>0.795<br>0.853 | 0.729 | 0.647 |
| **Effort Expectancy** | EE1<br>EE2<br>EE3 | 0.776<br>0.723<br>0.834 | 0.702 | 0.607 |
| **Social Influence** | SI1<br>SI2<br>SI3 | 0.802<br>0.854<br>0.844 | 0.782 | 0.695 |
| **Price Value** | PR1<br>PR2<br>PR3 | 0.804<br>0.843<br>0.831 | 0.771 | 0.685 |
| **Hedonic Motivation** | HM1<br>HM2<br>HM3 | 0.882<br>0.902<br>0.854 | 0.854 | 0.774 |
| **Habit** | H1<br>H2<br>H3 | 0.816<br>0.873<br>0.825 | 0.793 | 0.703 |
| **Facilitating Condition** | FC1<br>FC2 | 0.929<br>0.948 | 0.866 | 0.881 |
| **Information Quality** | IQ1<br>IQ2<br>IQ3 | 0.707<br>0.877<br>0.800 | 0.722 | 0.636 |
| **Intention** | BI1<br>BI3 | 0.870<br>0.826 | 0.712 | 0.720 |
| **Use Behaviour** | U1<br>U2<br>U3 | 0.834<br>0.771<br>0.833 | 0.784 | 0.689 |

Discriminant validity refers to the degree to which a construct is distinct from other constructs within a model. The Fornell-Larcker criterion is a widely used method for assessing the discriminant validity of latent constructs in a model. According to this criterion, discriminant validity is confirmed when the square root of the AVE value for each latent variable exceeds the correlational values between that latent variable and others in the model (Hulland, 1999). The table above displays the correlation values diagonally, where each is greater than the correlational values with other constructs. Therefore, discriminant validity is established in this model.

*TABLE 3: Heterotrait-Monotrait (HTMT) Ratio*

*Source: Smartpls4 Output*

| **Constructs** | **BI** | **EE** | **FC** | **H** | **HM** | **IQ** | **PE** | **PR** | **SI** |
|---|---|---|---|---|---|---|---|---|---|

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **BI** | | | | | | | | | |
| **EE** | 0.672 | | | | | | | | |
| **FC** | 0.854 | 0.552 | | | | | | | |
| **H** | 0.753 | 0.424 | 0.618 | | | | | | |
| **HM** | 0.619 | 0.353 | 0.542 | 0.403 | | | | | |
| **IQ** | 0.536 | 0.202 | 0.308 | 0.411 | 0.416 | | | | |
| **PE** | 0.400 | 0.312 | 0.193 | 0.192 | 0.294 | 0.234 | | | |
| **PR** | 0.696 | 0.274 | 0.560 | 0.783 | 0.634 | 0.398 | 0.301 | | |
| **SI** | 0.877 | 0.553 | 0.731 | 0.683 | 0.351 | 0.400 | 0.249 | 0.573 | |
| **U** | 0.520 | 0.442 | 0.269 | 0.173 | 0.325 | 0.216 | 0.176 | 0.118 | 0.209 |

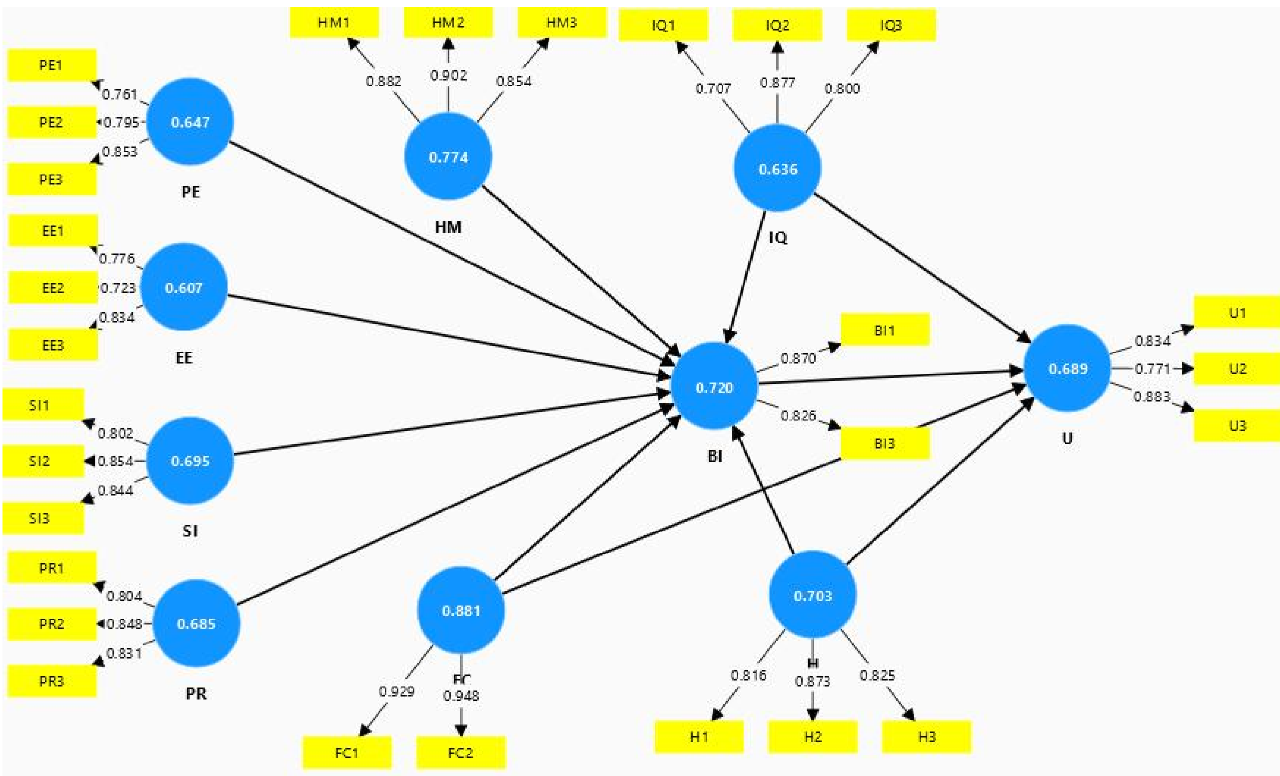


Figure 2: The Measurement Model highlighting Latent construct’s AVE values and item loading

Source: Smartpls4 Output

To evaluate the structural model, the study employed $R^2$ measure, a widely used metric for assessing structural models. This measure reflects the proportion of explained variance for all latent variables compared to their total variance. In this model, two endogenous variables—Intention to Use and Actual Use of ChatGPT—are analyzed. The adjusted $R^2$ value is 0.557 for Intention to Use (BI) and 0.752 for Actual Use (USE). This indicates that the final endogenous variable accounts for 75.20% of the variance, suggesting that the model's latent variables explain a significant portion of the variance. Additionally, the $f^2$ effect size assesses the influence of a particular exogenous latent variable on an endogenous variable [33]. The effect size determines the extent to which an independent latent variable significantly impacts a dependent variable. According to Nunnally & Bernstein, (1994), $f^2$ values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively. In this model, all the effect size values were either medium or large, indicating that the supporting variables have a considerable influence on explaining the endogenous variable.

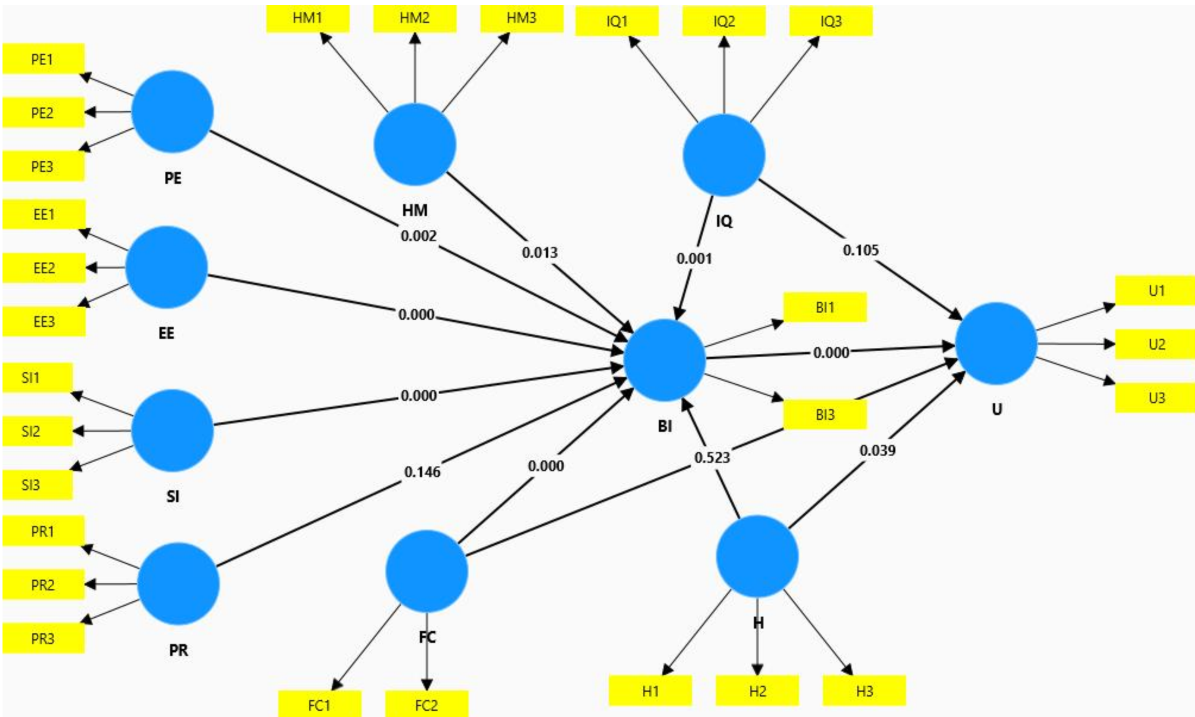


Figure 3: Structural model assessment

Source: SmartPLS4 Output

In smart PLS 4.0, the structural model was analyzed using the bootstrapping technique, where the significance of the t-statistics for the path coefficients was evaluated. Additionally, the values of the coefficients for various paths within the model reflected the strength of the relationships between the independent and dependent variables. To test the hypotheses, the bootstrapping method was employed with 5,000 subsamples.

Table 4: Results of hypothesis testing and structural relationships

Source: Smartpls4 Output

| **Hypothesis relationship** | **Hyp. No.** | **T statistics** | **P values** | **Result- Alternate Hypothesis** |
|---|---|---|---|---|
| PE -> BI | H1 | 3.045 | 0.002 | supported |
| EE -> BI | H2 | 3.912 | 0.000 | supported |
| SI -> BI | H3 | 5.114 | 0.000 | supported |
| FC -> BI | H4 | 4.870 | 0.000 | supported |
| FC -> U | H5 | 0.591 | 0.523 | Not supported |
| PR -> BI | H6 | 1.451 | 0.146 | Not supported |

| | | | | |
|---|---|---|---|---|
| HM -> BI | H7 | 2.472 | 0.013 | supported |
| H -> BI | H8 | 2.396 | 0.017 | supported |
| H -> U | H9 | 2.104 | 0.039 | supported |
| IQ -> BI | H10 | 3.349 | 0.001 | supported |
| IQ -> U | H11 | 1.587 | 0.105 | Not supported |
| BI -> U | H12 | 7.331 | 0.000 | supported |

The findings revealed that information quality, social influence, performance expectancy, hedonic motivation, effort expectancy, and habit significantly influence the behavioral intention to use ChatGPT. Additionally, both behavioral intention and habit have a direct and significant impact on the actual use of ChatGPT. The NFI, a goodness-of-fit measure introduced by Bentler-Bonett (1980) and also known as the Bentler-Bonett Normed Fit Index, assesses the chi-square value of the proposed model. For a model to be considered good, the NFI value should be close to 1. In this case, the NFI is 0.774, indicating that the model improves the fit by 77.4% compared to the null model.

Table 5: Mediation analysis

Source: Smartpls4 Output

| **H13: FC->BI X BI ->USE** | | | | | |
|---|---|---|---|---|---|
| | **Type of effect** | **T value** | **p value** | **Remarks** | **Result-Alternate Hypothesis** |
| **A** | Direct effect (FC ->BI) | 4.870 | 0.000 | **Full mediation** | **supported** |
| **B** | Indirect effect (FC->BIXBI->USE) | 4.207 | 0.000 | | |
| **C** | Total effect (FC ->USE) | 0.591 | 0.525 | | |
| **H14: H->BI X BI ->USE** | | | | | |
| | **Type of effect** | **T value** | **p value** | **Remarks** | **Remarks** |
| **A** | Direct effect (H ->BI) | 2.396 | 0.017 | **Complementary Partial mediation** | **supported** |
| **B** | Indirect effect (H->BI X BI ->USE) | 2.146 | 0.032 | | |
| **C** | Total effect (H ->USE) | 1.824 | 0.039 | | |
| **H15: IQ->BI X BI ->USE** | | | | | |
| | **Type of effect** | **T value** | **p value** | **Remarks** | **Remarks** |
| **A** | Direct effect (IQ ->BI) | 3.349 | 0.001 | **Full mediation** | **supported** |
| **B** | Indirect effect (IQ->BI X BI ->USE) | 2.985 | 0.003 | | |
| **C** | Total effect (IQ ->USE) | 0.111 | 0.105 | | |

Several studies has been identified where behavioural intention plays a mediating role between independent variable and actual use of technology (Venkatesh et al., 2003 and Venkatesh et al., 2012). In this study, significant mediating role of intention to use was found between Facilitating conditions and use and the said argument is also supported by Venkatesh et al., 2003 and 2012. Another relationship which depicts significant mediation by intention to use is shown between Information quality and actual use. Complementary partial mediation relation was established by intention to use between Habit and use of technology.

The above analysis offers a detailed summary of the constructs, indicators, and psychometric properties in a research study focused on understanding the factors that influence the intention to use ChatGPT from a youth perspective. The research model extends the UTAUT2 framework by incorporating Information Quality (IQ) as an individual determinant. Structural modeling and hypothesis testing reveal that hedonic motivation, performance expectancy, social influence, effort expectancy, information quality, and habit significantly contribute to ChatGPT usage. Mediation analysis indicates that the intention to use has a strong mediating effect on the actual use of ChatGPT. Overall, the study exhibits robust psychometric properties, effectively capturing the constructs associated with the intention to use ChatGPT.

In conclusion, this paper identifies key factors from the literature that are crucial for understanding the behavioural intention towards using ChatGPT. The study conceptualizes a new research framework to investigate the significant factors influencing the intention to use ChatGPT. Considering the widespread use of ChatGPT in India, especially in the Delhi-NCR region, understanding the determinants of learners' intentions is essential. The proposed research model validates the applicability of the UTAUT2 theory, along with the inclusion of information quality. The study's findings strongly indicate that hedonic motivation, performance expectancy, social influence, effort expectancy, habit, and information quality significantly impact students' intentions to use ChatGPT.

## V. FUTURE SCOPE OF THE STUDY

Future research should focus on longitudinal studies to track changes in user perceptions and behaviour over time, providing deeper insights into the evolving relationship between Millennial, Senior citizen and AI technologies like Chatbot. Additionally, exploring the role of individual differences, such as personality traits and digital literacy, could offer a more nuanced understanding of adoption patterns. Investigating the impact of emerging features and advancements in AI on user engagement and satisfaction will be crucial. Cross-cultural studies can shed light on how different cultural contexts influence the acceptance and use of ChatGPT. Lastly, integrating qualitative methods, such as in-depth interviews and focus groups, can enrich quantitative findings by capturing the nuanced experiences and motivations behind ChatGPT usage. This comprehensive approach will help developers create more user-centered and culturally adaptable AI applications.

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