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Multi-Stage Decision-Making in ChatGPT Adoption: A Cognitive Appraisal Perspective

Isha Srivastava[1], **Dr Ashish Kumar Singh**[2], **Dr. Anamika Pandey**[2], **Dr Suruchi Pandey**[3]*, **Dr Hemlata Gaikwad**[4]

[1]Research scholar, School of Business, Galgotias University;
[2]Professor, School of Business, Galgotias University;
[3]* Corresponding Author: Professor, Symbiosis Institute of Management Studies, Symbiosis International (Deemed University) suruchi.p@sims.edu
[4]Associate Professor, Symbiosis Institute of Management Studies, Symbiosis International (Deemed University)

ABSTRACT

This study aims to develop and empirically validate a comprehensive multi-stage decision-making (MSDM) model to explain users' intention to adopt ChatGPT (Generative AI). Based on cognitive appraisal theory, the model conceptualizes three stages of adoption: (Cognitive) primary appraisal, (emotional) secondary appraisal, and Physical outcome, integrating six key antecedents: social influence (SI), hedonic motivation (HM), facilitating conditions (FC), performance expectancy (PE), effort expectancy (EE), and emotion (EMO) on willingness to use or reject. Using data from 372 prospective ChatGPT users, the findings reveal that SI, HM, and FC positively influence PE and EE. In turn, PE and EE shape users' emotional responses, which ultimately determine their willingness or objection to adopt ChatGPT. The results show that ChatGPT adoption is a dynamic, stage-wise process driven by interconnected cognitive, motivational, and emotional factors. By offering a structured and integrative framework, this study advances understanding of GenAI adoption and offers valuable insights for researchers and practitioners to examine user behavior and design effective AI-enabled tools & services.

Keywords: cognitive appraisal theory, generative ai, multi-stage decision-making, technology adoption, user emotions

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INTRODUCTION

Generative AI (GenAI) has rapidly transformed human activities, from routine tasks to complex decision-making, by generating text, images, and technical content as needed (Menon & Shilpa, 2023; Wang et al., 2023). Its unprecedented growth has witnessed its widespread acceptance across various domains such as healthcare, tourism, and educational enhancement (Cascella et al., 2023; Uludag, 2023; Tian et al., 2023). Integrating GenAI into research writing content improved student achievement and consistency in learning outcomes (Nelson, 2026). Generative AI is increasingly relevant to international students in higher education across diverse learning environments, where they may rely on it for academic and information-related activities.

Despite these advantages, effective use of ChatGPT still requires appropriate input design and user skills, posing challenges for many users (Rudolph et al., 2023).

Prior research has explored various determinants of GenAI adoption, including perceived usefulness, ease of use, facilitating conditions, social influence, hedonic motivation, and trust (Vimalkumar et al., 2021; Duong, 2024; Tiwari et al., 2024; Bhat et al., 2024). Traditional models such as "Theory of reasoned action" (TRA), "Theory of planned behaviour" (TPB), "Technology Acceptance Model" (TAM), and "Unified Theory of Acceptance and Use of Technology" (UTAUT) have been widely applied to study technology adoption (Fishbein and Ajzen 1975; Ajzen, 1991; Davis, 1989; Venkatesh et al., 2003).

However, these models primarily focus on functional technologies and may not fully capture the complexity of human-like AI systems such as ChatGPT (Chan et al., 2017; Gursoy et al., 2019). Moreover, existing studies largely emphasise direct relationships between antecedents and behavioural intention, overlooking the dynamic, multi-stage nature of decision-making and the critical role of emotions.

Cognitive Appraisal Theory suggests that individuals' interpretations of a situation shape their emotional responses through primary (relevance) and secondary (evaluation) appraisal stages (Lazarus, 1991a; 1991b). Complementing this, Cognitive Dissonance Theory explains how inconsistencies between beliefs and experiences create psychological discomfort, prompting individuals to adjust their attitudes or behaviours (Festinger, 1962; Harmon-Jones, 2019). In one study, English language faculty have shown strong AI literacy but limited ethical readiness, focusing the need to integrate AI ethics into teacher education and professional development (Ayesha et al., 2026).

In the context of ChatGPT, users often experience both benefits and concerns (e.g., performance, effort, authenticity, and ethical issues), leading to acceptance or rejection decisions.

The UTAUT provides the foundation for users' initial technology-related appraisals through performance expectancy, effort expectancy, social influence, and facilitating conditions. The Cognitive Appraisal Theory explains how these appraisals generate subsequent evaluations and emotional responses. Cognitive Dissonance Theory talks about the final stage, where individuals reconcile conflicting cognitions and emotions, shaping their willingness to adopt or continue using ChatGPT. The proposed MSDM model integrates all three theories as per their explanatory roles across the decision process.

To address these gaps, this study integrates UTAUT constructs, i.e., performance expectancy, effort expectancy, social influence, and facilitating conditions, with cognitive and emotional perspectives to propose a multi-stage decision-making (MSDM) model. The model conceptualises ChatGPT adoption as a three-stage process: primary cognitive appraisal (evaluation of relevance and social context), secondary emotional appraisal (assessment of performance and effort), and outcome (emotion-driven behavioural intention). Thus, the theoretical contribution of this study lies in exploring how Generative AI users progress through sequential appraisal stages, rather than identifying additional predictors of technology adoption. Rather, the contribution lies in extending Lazarus's Cognition–Motivation–Emotion framework to the context of ChatGPT adoption among developing demographics by conceptualizing adoption as a sequential appraisal process. Unlike conventional UTAUT/TAM models, this study explains how users progressively

move from contextual and cognitive appraisals to emotional responses and ultimately to both willingness and objection toward ChatGPT adoption.

Currently, research on international students has increasingly focused on the importance of digital technologies in supporting learning, communication, and development within higher education. Generative AI may be particularly relevant in such contexts for learning assistance across diverse educational and linguistic settings. However, the present study does not focus specifically on international students; rather, it examines ChatGPT users in general. Consequently, this research can be extended to future research for international-student is same domain.

Accordingly, this study addresses the following research questions:

RQ1: How do sequential cognitive appraisals and emotional responses affect ChatGPT users' stage-wise adoption process?

RQ2: How do primary cognitive appraisal factors affect individuals' secondary cognitive appraisals during ChatGPT adoption?

RQ3: How do emotional responses mediate the relationship between cognitive appraisals and users' willingness to accept/reject ChatGPT?

The objective of this study is to examine the stage-wise adoption of ChatGPT by identifying key factors influencing user decisions, understanding how these factors shape users' positive and negative emotions, and analysing how users progress through a multi-stage decision-making process leading to acceptance or rejection of ChatGPT adoption.

By offering a structured, stage-based framework, this research advances the understanding of GenAI adoption and provides actionable insights for academics and practitioners to design more effective and user-centric AI-enabled services.

The remainder of the paper is organised as follows. The literature review examines prior studies on users' behavioural intentions toward ChatGPT and integrates Lazarus's cognition–motivation–emotion framework (1991a) to develop the proposed model. The methodology section outlines the data collection and research design used to test the model. This is followed by the results and discussion. Theoretical and managerial implications are then presented, and the paper concludes with limitations and directions for future research.

LITERATURE REVIEW AND THE THEORETICAL BACKGROUND

Willingness to Accept and Use ChatGPT

However, understanding the variables influencing users' willingness is a complicated process. As per the "Theory of Reasoned Action" (Fishbein & Ajzen, 1975), intention/willingness to use is a crucial antecedent of an individual's actual behaviour. Previous studies have verified many variables that influence users' willingness to adopt ChatGPT (Gen AI), like "anthropomorphism", "reactivity" and "intelligence", significantly impact the adoption of AI (Wu et al., 2023; Fernandes & Oliveira, 2021; Lu et al., 2019). Variables like "perceived usefulness", "ease of use", "risk", and "trust", shape user's attitudes (Davis, 1989; Vimalkumar et al., 2021). Some external variables like "marketplace dynamics", "privacy concerns", and "ethical considerations" also facilitate or discourage AI adoption (Klaus & Zaichkowsky, 2022; Sharma et al., 2022). In addition, some user characteristics like "demographics", "personality traits", "innovativeness", and "prior experience" also impact AI adoption (Liu & Tao, 2022; Venkatesh et al., 2003). TAM and UTAUT with extended variables have also been checked to impact the adoption of ChatGPT (Ma et al., 2024; Menon & Shilpa, 2023). The study explored the adoption of GenAI technologies among students and lecturers in higher education through the lens of the UTAUT and found performance expectancy to be the strongest predictor for ChatGPT (Ayalon & Ido, 2026). In the study done by Yang (2026), a systematic literature review analysed 54 empirical studies that verified the acceptance and use of ChatGPT by students in various places in higher education and summarized how various key variables

affect learners' behavioural intention and use behaviour. In one study, researchers examined the role of emotional experiences and cognitive evaluations that affect faculty willingness to use ChatGPT in their daily teaching practices (Wang et al., 2026).

In the study regarding the adoption of Gen AI, among U.S. students, it was found that to build attitudes toward GenAI use, perceived ease of use, perceived usefulness, perceived enjoyment, novelty, trust towards technology, subjective norms, and AI literacy played a positive role (Ittefaq et al., 2025). In another related study, it was verified how perceived usefulness, personalization, influence on decision-making, and trust were used as powerful tools for recruitment of international students based on TAM theory, Trust-Based Decision-Making Model, and the Personalization–Privacy Paradox (Dmour et al., 2025). Additionally, some recent studies highlighted that perceived risk, privacy, algorithmic transparency**,** and ethical concerns regarding bias, accountability, and misuse effect user's adoption decisions and confidence (Dwivedi et al., 2023).

But existing previous studies have mainly explained ChatGPT adoption using TAM, UTAUT2, and AI acceptance frameworks, highlighting factors as direct determinants of behavioural intention (Davis, 1989; Venkatesh et al., 2003; Venkatesh et al., 2012, Kutty et al 2026). These models effectively identify what factors drive technology adoption; rather, they give limited insight into how individuals move through the cognitive and emotional processes leading to acceptance or rejection. Similarly, the "Stimulus–Organism–Response (SOR)" framework explains users' behavioural responses through interactions between external stimuli and internal psychological states (Mehrabian & Russell, 1974), whereas "Expectation Confirmation Theory (ECT)" mainly highlights users' post-adoption satisfaction and continuance intentions (Bhattacherjee, 2001). In contrast, "Lazarus's Cognition–Motivation–Emotion framework" conceptualizes adoption as a dynamic appraisal process in which cognitive evaluations shape emotional responses and further to influence behavioural decisions (Lazarus, 1991a). This study integrated UTAUT constructs within the appraisal-based framework to provide a process-oriented explanation of ChatGPT adoption, offering valuable insights into the cognitive–emotional mechanism to accept or reject ChatGPT as a dual outcome that conventional UTAUT models cannot fully explain (Gursoy et al., 2019; Roy et al., 2020).

Unlike traditional models, which mainly explain adoption intention through technological and social factors, the MSDM framework captures initial technology-related appraisals with secondary cognitive evaluations, emotional responses, and final willingness/objection to use ChatGPT. Thus, the framework integrates cognitive and affective mechanisms together to explain how users progress through different stages of the adoption decision of Gen AI.

However, the "Cognitive Appraisal Theory" says that a user's reactions to a stimulus are shaped by emotions that occur during multi-stage cognitive evaluations of the insight (Lazarus, 1991a; Breitsohl & Garrod, 2016), and it is used to explain the coping behaviours for complex decisions (Breitsohl & Garrod, 2016; Lu et al., 2019). Hence, most likely, an individual's final decision to accept/reject the use of ChatGPT (GenAI) tools will be decided by their emotions, resulting from several multi-stage assessment processes (Gursoy et al., 2019; Bhuiyan et al., 2024, Pandey et al 2026).

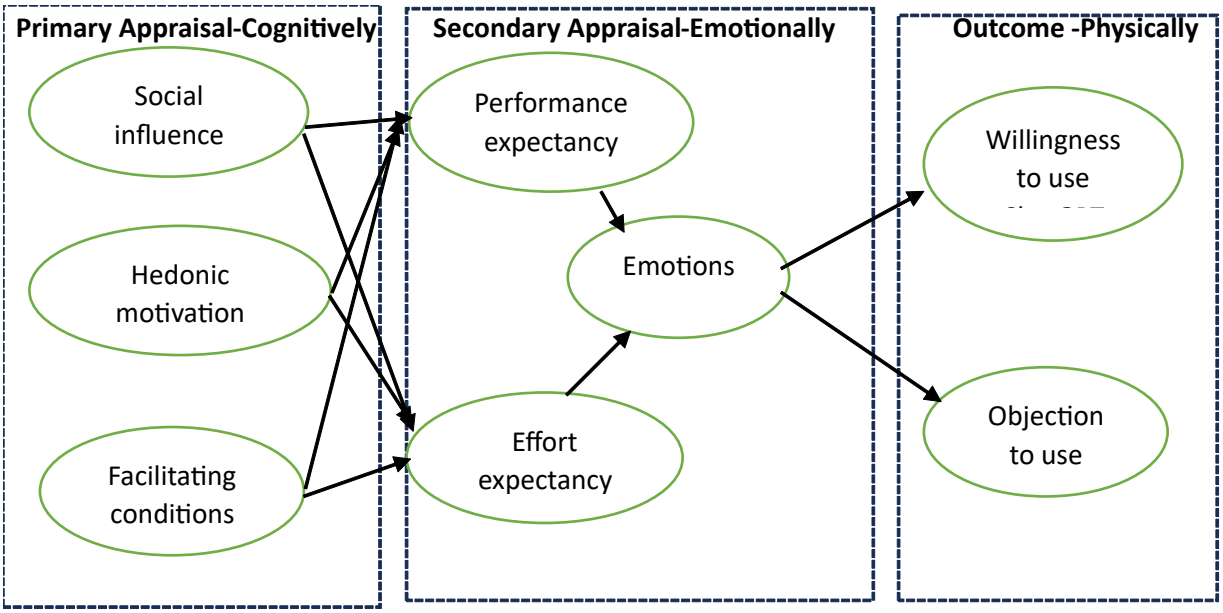


Figure 1

The Proposed Model

The 3-Stage Appraisal Phases of Adoption/Rejection

This study uses Lazarus's "cognition-motivation-emotion" framework (1991a), and the important antecedents of the user's inclination to integrate ChatGPT (GenAI) based on a recent study by Huy et al. (2024). This study proposes that users move through several stages of the decision-making process, which include evaluation of the relevance and importance of ChatGPT (primary appraisal), secondary stages are analysing the perceived advantages ("performance expectancy") with efforts and cost ("effort expectancy") of using ChatGPT, which leads to the creation of emotions, and finally reflects in terms of behavioural outcome as a willingness/objection to use ChatGPT. The whole process has been described in Fig. 1. As per our proposed model, in the first/primary evaluation stage, users judge the applicability, utilisation, and importance of using ChatGPT tools for their use, based on factors: "facilitating conditions", "social influence", and "hedonic motivation". After their primary appraisal, users who find the use of ChatGPT useful and important will carry out a purposeful evaluation of advantages and costs based on PE and EE, which leads to the creation of emotions toward ChatGPT similar to another study for the adoption of AI devices (Lazarus, 1991a; Gursoy et al., 2019; Bhuiyan et al., 2024). Finally, users' emotions will shape their interest/objection to accept/reject the use of ChatGPT tools.

The Primary Appraisal Phase

Before adopting AI tools like ChatGPT, users assess their relevance and congruence with personal needs (Lazarus, 1991b; Gursoy et al., 2019; Bhuiyan et al., 2024). If misaligned with expected outcomes, no emotional response occurs.

The study identifies three key factors shaping this primary judgment—social norms, hedonic motivation, and facilitating conditions (Huy et al., 2024; Gursoy et al., 2019; Bhuiyan et al., 2024). If these align with user expectations, they proceed to a second stage, evaluating the costs and benefits of using AI tools (Lazarus, 1991a; Gursoy et al., 2019; Bhuiyan et al., 2024).

Social Influence (SI). Social Influence (SI) refers to users' perception that using ChatGPT aligns with the norms of their close social groups (family, friends, classmates) and which develop behavioural intentions (Latané, 1981; Rather, 2018), and tend to adopt their values and beliefs (Jeon et al., 2018). If peers view ChatGPT as beneficial, they encourage its use, leading to favourable attitudes.

SI can reduce perceived risks and adoption barriers (Mogaji et al., 2021; Terblanche and Kidd, 2022). Prior studies also confirm SI as a key driver of technology and AI adoption, including ChatGPT (Hsu et al., 2017; Jain et al., 2022; Gursoy et al., 2019; Bhuiyan et al., 2024; Roy et al., 2024; Menon and Shilpa, 2023; Huy et al., 2024). Thus, approval from close social groups increases adoption likelihood, and its impact on first-stage positive perception is hypothesised.

H1. Social influence significantly influences performance expectancy of ChatGPT use.

Effort Expectancy (EE). Effort Expectancy (EE) refers to how easy (Venkatesh et al., 2012) or difficult (Gursoy et al., 2019) users perceive a technology, i.e., ChatGPT, to use and its utility related to cost-benefit analysis (Roy et al., 2020). Here in this study, we used the operational definition of EE as perceived easiness to use of GenAI. According to UTAUT, EE depends on factors such as prior experience, technical skills, system complexity, and resource availability (Muriithi et al., 2016). In this study, if users find ChatGPT easy to use and less costly, they are more likely to adopt it.

While some studies report a negative effect of EE on chatbot adoption (Henkel et al., 2022; Melián-González et al., 2021), others show a positive impact on ChatGPT (Jain et al., 2022; Gursoy et al., 2019; Bhuiyan et al., 2024; Roy et al., 2024; Huy et al., 2024).

As per Lazarus's framework, EE is shaped by social influence. If users' social group perceives ChatGPT as easy and less complex, then users are also going to perceive it as less difficult and value for money. So, we can conclude that social influence reduces users' EE towards ChatGPT. Based on this, a hypothesis is proposed.

H2. Social influence significantly influences effort expectancy toward ChatGPT use

Hedonic Motivation (HM). Hedonic Motivation (HM) refers to the enjoyment or pleasure users experience when using ChatGPT and other AI applications (Farzin et al., 2021). It is a key predictor of technology adoption behaviour (Tamilmani et al., 2019; Venkatesh et al., 2012) and influences users' willingness to adopt ChatGPT (Huy et al., 2024).

Users with stronger hedonic motives are more likely to develop favourable perceptions, including higher performance expectancy (Gursoy et al., 2019; Bhuiyan et al., 2024; Roy et al., 2024; Yadegaridehkordi et al., 2026). Based on this, a hypothesis is proposed.

H3. Hedonic motivation (HM) significantly influences performance expectancy (PE) towards ChatGPT use.

User stimulus acts as a compensatory mechanism in managing task complexity (Hockey, 1997). Earlier studies show that task demands and complexity influence perceived cognitive effort (Humphreys & Revelle, 1984), and motivation is linked to perceived task difficulty (Capa et al., 2008; Gendolla & Wright, 2005). Individuals with strong hedonic motivation are more likely to trust technology (Baabdullah, 2018).

Recent studies report mixed effects of hedonic motivation on effort expectancy (Bhuiyan et al., 2024; Gursoy et al., 2019; Roy et al., 2024). However, it can be inferred that highly hedonic motivated users perceive AI tools as less difficult and more cost-beneficial. Venkatesh et al. (2012) discussed that intrinsic enjoyment due to HM encourages users to use more technology by making them more familiar, and make them to appear less difficult, and improving effort expectancy.

Hedonic Motivation as the enjoyment or pleasure derived from using a technology. When users experience enjoyment and have fun while using ChatGPT, they are more willing to explore it by spending

more time, overcoming minor usability difficulty & challenges, and perceive less costly and more engaging (Hsiao and Chen 2016). Hence, the hypothesis is proposed.

H4. Hedonic motivation significantly influences effort expectancy toward ChatGPT use**.**

Facilitating Conditions (FC). Facilitating Conditions (FC) refer to the extent to which users perceive the availability of resources and support needed to use a technology (Venkatesh et al., 2003). In information systems, FC include factors such as time, financial resources, skills, and regulations that reduce barriers to use and enhance adoption intentions (Hu et al., 2020; Thompson et al., 1991; Venkatesh et al., 2003). Prior studies show a positive relationship between FC and technology usage (Oliveira et al., 2014; Hsu et al., 2017; Haller et al., 2021; Jain et al., 2022).

Hence, we proposed the hypothesis

H5. "Facilitating conditions significantly influence performance expectancy toward ChatGPT use".

Nowadays, users have prior experience, technical skills, and knowledge, and sufficient support and facilities to use complex tools, so users are perceiving less difficulty in using new technologies like Gen AI (Muriithi et al, 2016). Since ChatGPT is a trained language model with less effort expectancy for its usage. Finally, EE can be understood as an important factor in the promotion and adoption of ChatGPT. Hence, we can propose the hypothesis

H6. "Facilitating conditions significantly influence effort expectancy toward ChatGPT use"

Secondary Appraisal Stage (SAS)

During the secondary appraisal stage (SAS), users form emotions toward ChatGPT by evaluating its costs and benefits through performance expectancy (PE) and effort expectancy (EE) (Venkatesh et al., 2012). Consistent with prior AI studies, PE and EE are key factors in this evaluation (Lu et al., 2019; Gursoy et al., 2019; Bhuiyan et al., 2024; Roy et al., 2024).

According to Cognitive Dissonance Theory (Festinger, 1962), users tend to maintain consistency with their initial attitudes, positive or negative, formed during the primary stage. If ChatGPT is perceived as fast, accurate, reliable, and easy to use (high PE and EE), users develop favourable emotions in hospitality contexts (Lu et al., 2019; Gursoy et al., 2019; Bhuiyan et al., 2024; Roy et al., 2024).

In UTAUT, PE reflects the extent to which users believe ChatGPT enhances task performance, shaped by its perceived usefulness, capability, and alignment with work practices, leading to corresponding emotional responses.

So, based on the above, we can propose the hypothesis;

H7. "Performance expectancy significantly influences users' emotional responses toward ChatGPT use."

Users often face difficulties in providing accurate inputs to ChatGPT, requiring skills, training, and effort to obtain relevant outputs. This can create confusion and increase perceived effort (Thompson et al., 1991), leading to negative emotions, and vice versa (Lazarus, 1991b). Similar findings are reported in AI device and hospitality studies (Gursoy et al., 2019; Bhuiyan et al., 2024; Roy et al., 2024). Hence, the hypothesis is proposed.

H8. Effort expectancy significantly influences users' emotional responses toward ChatGPT use.

Outcome Stage (OS)

After evaluation, users develop emotions that influence their acceptance or rejection of ChatGPT. Positive emotions such as happiness, pleasure, and satisfaction encourage usage behaviour (Watson & Spence, 2007). According to Cognitive Appraisal Theory, favourable emotions increase the likelihood of adoption, as supported in studies on AI devices and hospitality (Gursoy et al., 2019; Bhuiyan et al., 2024; Roy et al., 2024).

Hence, the proposed hypothesis is as follows:

H9. "Emotion has a significant influence on the user's willingness to accept the use of ChatGPT".

Disapproval of ChatGPT refers to users' unwillingness to use it, often arising from emotions such as frustration, uncertainty, and worry during decision-making (Raghunathan & Pham, 1999; Rucker & Petty, 2004). According to Cognitive Appraisal Theory, such emotions can lead to rejection of technologies. Prior studies also show that negative emotions drive resistance to AI adoption in services and hospitality (Chen & Granitz, 2012; Gursoy et al., 2019; Bhuiyan et al., 2024; Roy et al., 2024).

Based on the available empirical studies, the following hypothesis is proposed:

H10. "Users' emotional responses significantly influence objections to ChatGPT use"

METHOD

Research Design and Survey Instruments

This study followed a quantitative approach by using a structured questionnaire, and it was developed by following a multi-stage process. First, the study's relevant constructs were identified based on the proposed conceptual framework and theories. Measurement items were adapted from previously validated and published scales in the literature, with some modified wording to suit the ChatGPT context by preserving the original meaning. A five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree) was used to measure all constructs. Subject experts reviewed the drafted questionnaire to ensure content validity and improve clarity and relevance. A pilot study was subsequently conducted with a small group of 40 ChatGPT users to check ambiguities and verify the clarity, readability, completion time, and reliability of the instrument. The pilot results showed satisfactory internal consistency (Cronbach's $\alpha > 0.70$ for all constructs), and some minor revisions were made before administering the final questionnaire to the target respondents.

Two sections- demographics (gender, age, occupation, education) and main items measuring study constructs were designed.

Details of measurement scales were adapted from prior studies. Constructs included social influence (3 items), hedonic motivation (4), facilitating conditions (4), performance expectancy (3), effort expectancy (3), emotion (4), willingness to adopt (3), and rejection (3), sourced from UTAUT (Venkatesh et al., 2012; Huy et al., 2024; Bhuiyan et al., 2024; Roy et al., 2024) and AIDUA (Gursoy et al., 2019). Emotions were measured using a 5-point bipolar scale (e.g., "bored/relaxed or unsatisfied/satisfied"), while other items used a 5-point Likert scale. A pilot study was conducted to refine the questionnaire and improve reliability.

Details of Sample and Collection of Data

The proposed hypotheses were tested using data collected from ChatGPT users across India through online questionnaires. India was chosen due to its large tech-savvy population, diverse user base, growing internet usage, and expanding AI market (Arora & Dhole, 2019; Kshetri, 2023; Menon & Meghana, 2021; Sharma & Sood, 2022; Menon & Shilpa, 2023).

Data were collected using non-probability purposive sampling to target users with prior ChatGPT experience, ensuring that the respondents possessed the necessary knowledge to evaluate the constructs meaningfully. Respondents were approached via personal contacts and professional social media channels after their consent. No monetary incentives were provided. Based on 26 items, a minimum sample size of 260 was required (Bollen, 1989), but a larger sample was collected to enhance reliability.

A total of 540 respondents were approached for data collection; out of these, 402 responses were received, and finally 372 valid responses were used after data cleaning and incomplete responses were eliminated, so the response rate was 74.44%. The survey was done during the months of January-March 2026. Therefore, no data imputation process was required. Some attention-check questions increased data quality, and the final sample was adequate for CB-SEM analysis (Ringle et al., 2016). Basic demographic details (gender, age, and profession) are presented in Table 1.

Ethical Approval

Formal ethical approval was not received, as there is no such committee at the university. However, the study adhered to research ethical principles involving human respondents. Before completing the questionnaire, respondents were provided with an informed consent statement explaining the study's purpose, their voluntary participation, anonymity, confidentiality of their responses, and the right to withdraw from the survey at any time. Completion of the questionnaire was considered evidence of informed consent.

Data Analysis

The proposed model was tested using SmartPLS in two steps. First, confirmatory factor analysis (CFA) assessed the proposed model fit. Then, the structural model examined the direction and strength of relationships using PLS-SEM. This was employed because the study aims to explore a complex stage-wise cognitive appraisal framework by integrating constructs from several theoretical perspectives to understand ChatGPT adoption behaviour. Additionally, it also aims to examine sequential cognitive appraisal and emotional mediation in an emerging technology context. Compared with covariance-based SEM, PLS-SEM is found to be more suitable for analysing complex models, maximizing the explained variance of endogenous constructs, and providing prediction-oriented research (Hair et al., 2022; Sarstedt et al., 2022). Hence, SmartPLS 4 was considered to be an appropriate analytical approach for the study. The measurement and structural models were verified, with bootstrapping of 5000 subsamples, for a two-tailed 5% significance level to test the proposed hypothesis.

Common Method Bias

To reduce common method bias, confidentiality was assured, only experienced ChatGPT users were included via a filter question, and diverse respondent groups were approached to fill the questionnaire (Table 1).

To test the Common method bias issues, Harman's single-factor test was conducted and found that the first factor accounted for 43.489% (less than 50%) of the total variance, indicating that common method bias is not a significant concern (Harman, 1967; Podsakoff et al., 2003).

RESULTS

Demographic Details of the Survey Respondents

Respondents included 170 females (45.69%) and 202 males (54.30%). Most were aged 18–25 (65.86%), followed by 26–35 (19.62%) and above 36 (14.24%).

In terms of education, 51.61% were graduates, 43.01% postgraduates, 4.30% intermediate, and 1.07% held other diplomas. Regarding employment, 47.84% were students, 43.01% employees, 7.52% entrepreneurs, and 1.34% others.

The study reports demographic characteristics of the respondents. Future studies may add some more technology usage characteristics, such as users' frequency of use and prior AI experience for GenAI, and primary purpose to use GenAI, to provide a richer description of the sample.

Table 1

Socio-demographic Details

Socio-demographic details		Frequency (n)	Percentage (%)
Gender	Male	202	54.30
	Female	170	45.70
Age	18-25 years	245	65.86
	26-36 years	73	19.62
	≥ 36 years	53	14.25
Education	Intermediate	16	4.30
	Graduation	192	51.61
	Post Graduation	160	43.01
	Others	4	1.08
Occupation	Students	178	47.85
	Employees	160	43.01
	Entrepreneurs	28	7.53
	Others	5	1.34

Measurement Model (MM) Assessment

The measurement model was validated using CFA. Normality was confirmed as skewness and kurtosis values were below 2 (Thompson, 2004; Hair et al., 2011). Convergent validity was assessed using AVE, composite reliability (CR), and outer loadings.

Outer loadings ranged from 0.739 to 0.910 (≥ 0.5), and all path coefficients were significant ($p < 0.00$). Cronbach's alpha values exceeded 0.70, indicating reliability, while AVE values were above 0.50, confirming convergent validity (Fornell & Larcker, 1981; Hair et al., 2011).

Table 2

The Scores of the Measurement Scale of Constructs and Items Used

Constructs and their items	**"Item's Loadings"**	**"Cronbach's alphas (α)"**	**AVE**

"Social influence" (SI) (Venkatesh et al. 2012; Gursoy et al., 2019; Duong, 2024)		0.881	0.808
Using ChatGPT among friends, relatives, and colleagues reflects status symbols	0.907		
Important people near me encourage me to use ChatGPT	0.906		
People in my social networks are of high profile who use ChatGPT	0.882		
"Hedonic motivation" (HM) (Venkatesh et al. 2012; Gursoy et al., 2019; Duong, 2024)		0.895	0.761
Using ChatGPT is entertaining	0.870		
Using ChatGPT is enjoyable	0.892		
Interaction with ChatGPT is fun	0.894		
ChatGPT gives me fun while using it	0.832		
"Facilitating Conditions' (FC) (Menon and Shilpa 2023; Duong, 2024)		0.885	0.813
ChatGPT provides crucial resources for our use	0.910		
I possess the required skills to use ChatGPT.	0.903		
I found ChatGPT more compatible with my service use	0.892		
"Performance expectancy" (PE) (Gursoy et al., 2019; Duong, 2024)		0.790	0.704
I found ChatGPT useful in my routine work	0.871		
ChatGPT increases my efficiency and provides accurate information	0.819		
ChatGPT allows me to do my tasks more swiftly and without errors.	0.827		
"Effort expectancy" (EE) (Venkatesh et al., 2012; Yadegaridehkordi et al., 2026)		0.844	0.762
I can easily understand and interact with ChatGPT	0.852		
I can easily learn to use ChatGPT	0.905		
I can skillfully use ChatGPT	0.862		
"Emotions" (EMO) (Gursoy et al., 2019; Bhuiyan et al., 2024)		0.845	0.684
Bored-relaxed	0.853		
Unsatisfied-satisfied	0.865		
Despairing-hopeful	0.844		
Annoyed-pleased	0.739		
"Willingness to use ChatGPT" (WTU) (Gursoy et al., 2019; Bhuiyan et al., 2024)		0.856	0.775
I am willing to get ChatGPT tools and services	0.873		
I will be glad to use ChatGPT.	0.883		
I want to use ChatGPT	0.885		

"Objections to using ChatGPT" (OTU) (Marikyan et al. 2020; Ranjan & Mukherjee 2026**)**		0.832	0.747
I have doubts about using ChatGPT, despite its potential benefits.	0.889		
I remain confused about whether I should use ChatGPT.	0.876		
I have hesitation about using ChatGPT.	0.827		

As per Table 3, the square roots of AVE values are more than the score of correlation among themselves for all constructs, indicating desirable discriminant validity (Hair et al., 2014).

Table 3

Discriminant Validity - Fornell-Larcker Criterion & Heterotrait-Monotrait Ratio (HTMT)

	EE	**EMO**	**FC**	**HM**	**PE**	**SI**	**OTU**	**WTU**
EE	**0.873**	0.698	0.499	0.596	0.901	0.585	0.717	0.615
EMO	0.597	**0.827**	0.494	0.715	0.715	0.578	0.623	0.514
FC	0.431	0.431	**0.901**	0.513	0.545	0.484	0.465	0.381
HM	0.523	0.618	0.453	**0.872**	0.675	0.553	0.654	0.544
PE	0.738	0.590	0.453	0.571	**0.840**	0.641	0.780	0.636
SI	0.504	0.499	0.428	0.490	0.537	**0.898**	0.626	0.559
OTU	0.608	0.535	0.404	0.567	0.638	0.540	**0.864**	0.517
WTU	0.523	0.438	0.334	0.476	0.529	0.486	0.441	**0.880**

Note. Above and below the diagonal are HTMT and FC values, respectively.

As per Table 3, a construct's AVE score should be higher than its associated constructs (Fornell and Larcker, 1981), and confirms that all the scores of constructs are less than 0.9 (Henseler et al., 2015), ensuring good discriminant validity among constructs.

Since all the scores of "variance inflation factor" (VIF) range from 1.575 to 2.861 (≤3.3) (Petter et al., 2007), there is no issue of multicollinearity.

Assessment of the Structural Model

CFA results confirm that the measurement model is valid and reliable. Model fit was assessed with $\chi^2 = 1408.03$ and df = 506, yielding $\chi^2/df = 2.78$ (< 3), indicating a good fit (Kline, 2005). Additionally, SRMR = 0.049 (≤ 0.08) and NFI = 0.83 (close to 0.9) further support model adequacy (Bentler & Bonett, 1980).

Hypotheses Results

SMARTPLS was used to test the hypotheses (Hair et al., 2011). Table 4 presents β, t-values, p-values, and f^2.

Table 4

Direct Effects, Path Coefficients, and Hypothesis Status

Hypothesis	**Beta (β)**	**f^2**	**f2 interpretation**	**t-score**	**p-value**	**Result**

SI—PE	0.294	0.108	Small	5.694	0.000	S
SI—EE	0.280	0.088	Small	4.276	0.000	S
HM—PE	0.351	0.148	Small	5.65	0.000	S
HM—EE	0.309	0.106	Small	4.523	0.000	S
FC--PE	0.169	0.038	Small	3.22	0.001	S
FC--EE	0.172	0.035	Small	2.523	0.012	S
PE--EMO	0.328	0.082	Small	3.967	0.000	S
EE-EMO	0.350	0.097	Small	4.807	0.000	S
EMO--WTU	0.537	0.237	Large	6.562	0.000	S
EMO--OTU	0.535	0.402	Medium	10.759	0.000	S

Note. S = supported; the above hypotheses were tested at a 95% confidence level for two tails.

As shown in Table 4, all hypotheses were supported. Social influence positively affected PE (β=0.294, $p < 0.001$) and EE (β=0.289$p < 0.001$). Hedonic motivation positively influenced PE (β=0.349, $p < 0.001$) and EE (β=0.309, $p < 0.001$). Facilitating conditions positively impacted PE (β=0.170, $p < 0.001$) and EE (β=0.172, $p < 0.001$).

PE positively influenced emotions (β=0.328, $p < 0.001$), while EE (β=0.350, $p < 0.001$). Emotions, in turn, increased willingness to use ChatGPT (β=0.537, $p < 0.001$) and objections to use (β=0.437, $p < 0.001$).

Effect sizes (f^2) were examined to assess the significance of each structural relationship. The results show that the relation from EMO—WTU is large, EMO—OTU is medium, and the rest are small, as per the threshold values of ≤0.02 no effect, 0.02 to 0.14 small, 0.15 to 0.34 medium, and ≥0.35 large effects (Table 4) (Cohen, 1988; Hair et al., 2022).

The values of R^2 are as follows: 42% variance in PE, 37% in EE, 40.4% in emotions, 28.67% in willingness, and 18.9% in objections. Some values are moderate because the predictive power reflected the multifaceted nature of ChatGPT adoption, which is affected by some more additional factors such as individual, technological, and contextual factors, which are not incorporated in the present model.

The Q^2 values show that the model demonstrates medium predictive relevance for WTO (Q^2 = 0.206) and small predictive relevance for WTU (Q^2 = 0.142). Overall, the positive Q^2 values indicate that the model has satisfactory predictive relevance for both endogenous constructs (Hair et al., 2022).

All hypotheses were developed based on strong theoretical foundations and prior empirical evidence rather than exploratory assumptions. Nevertheless, we acknowledge that complete support for the proposed relationships may be influenced by the study context and sample characteristics. Accordingly, we have moderated our interpretation of the findings and added this as a limitation, recommending that future studies validate the proposed framework across different populations and contexts.

DISCUSSION

The results support the proposed three-stage adoption model of ChatGPT. In the primary stage, social influence (SI), hedonic motivation (HM), and facilitating conditions (FC) shape users' evaluations. Positive evaluations enhance performance expectancy (PE) and effort expectancy (EE), leading to favourable emotions in the secondary stage, which then drive behavioural intentions, consistent with Lazarus's framework (Lazarus, 1991).

The strong impact of HM on PE suggests that users who find ChatGPT enjoyable and engaging are more likely to perceive it as beneficial and perceive to enhance their performance. This finding is consistent with Gursoy et al. (2019), who also found that HM positively influenced PE in AI acceptance. Further, positive emotions shaped by favourable cognitive appraisals may strengthen willingness to use ChatGPT, whereas, on the other hand, negative emotions may reinforce objections and reduce willingness.

Social groups significantly influence users' attitudes, especially for less experienced users (Venkatesh & Davis, 2000; Althuizen, 2018; Roy, 2024), supporting social identity theory and prior ChatGPT studies (Menon & Shilpa, 2023; Huy et al., 2024). HM is the strongest predictor, positively affecting PE and EE (Yadegaridehkordi et al., 2026), aligned with cognitive dissonance theory (Festinger, 1962). FC also supports improving PE and EE, which is aligned with the previous study (Thompson et al., 1991; Venkatesh et al., 2003; Oliveira et al., 2014; Hsu et al., 2017; Hu et al., 2020; Haller et al., 2021; Jain et al., 2022).

PE and EE shape emotions, with PE having a stronger effect. Emotions strongly influence willingness to adopt ChatGPT, consistent with prior AI studies (Lu et al., 2019; Gursoy et al., 2019; Bhuiyan et al., 2024). Overall, willingness to adopt is higher than resistance despite concerns about ethics and reliability, confirming that users see more benefits from GenAI.

Although all hypothesized relationships were supported, the model was theory-driven and specified a priori, reducing the likelihood of overfitting. Furthermore, procedural and statistical assessments indicated minimal common method bias, although some relationship inflation inherent to self-reported cross-sectional data cannot be entirely ruled out.

Theoretical Contribution

This study contributes to GenAI adoption literature by validating key antecedents of ChatGPT use: SI, HM, FC, PE, EE, emotions, and willingness or objection to use. It also explains the integration of the multi-stage decision-making process, aligning with cognitive appraisal theory in shaping adoption intentions. This process-oriented perspective provides a better understanding of the psychological adoption mechanism than traditional models that do not explicitly capture the appraisal–emotion pathway or dual behavioural outcomes.

Unlike traditional models such as TAM and UTAUT, which focus on non-intelligent technologies (Chan et al., 2017), this study highlights their limitations in the context of AI and GenAI (Gursoy et al., 2019). It advances understanding by modelling adoption as a step-wise, sequential, interdependent process rather than isolated relationships by highlighting cognitive-emotional stages to adoption/rejection of GenAI.

Theoretically, this study extends conventional technology-adoption models by conceptualizing ChatGPT adoption as a sequential decision-making process. By integrating UTAUT factors with Cognitive Appraisal Theory and Cognitive Dissonance Theory, the proposed MSDM framework distinguishes primary and secondary cognitive appraisal steps and explains how these evaluations generate emotional responses that subsequently shape users' willingness and objections toward ChatGPT. Thus, the study extends technology-adoption research by integrating cognitive, affective, and decision-making processes within a unified framework.

Managerial Implications

With the rapid growth of GenAI, organisations are investing heavily to improve efficiency and reduce administrative costs. However, findings suggest users are not uniformly willing to adopt ChatGPT, so companies must first try to understand user needs before making large investments. Social and hedonic motivations are critical; firms should leverage peer influence in promotions, as references from early users of GenAI can build trust, reduce perceived effort, and encourage adoption.

Enhancing hedonic aspects, such as enjoyment, engagement, and interactivity, can develop positive user emotions. So, the services should be responsive, supportive, personalised, and emotionally engaging. Additionally, improving facilitating conditions is essential: clear guidance, reliable and authentic outputs, local language support, and reduced learning & usage effort can enhance performance expectancy and ease of use.

The study highlights that ChatGPT adoption is a multi-stage process, where users first assess the relevance of the tools and ease, then evaluate benefits and effort, leading to emotions that shape willingness

or resistance. So, firms should design services accordingly. By focusing on India, the study also contributes to understanding user behaviour and supports the growth of the AI ecosystem, which is still in a very nascent stage.

CONCLUSION

This study proposed and verified a model to explore the 3-stage user's decision-making for adopting ChatGPT (GenAI) with interrelationships among crucial predictors. We identified six crucial predictors based on the literature, including SI, HM, FC, PE & EE, and emotion, for the adoption of GenAI, based on "cognitive appraisal theory". We learned the decision-making process at a very micro level, focusing on cognitive and emotional aspects, how the users evaluate the adoption of ChatGPT based on its importance, relevancy, utility, society, performance, effort required, facility availability, and shape their behavioural attitude to show willingness to use or reject the services.

Limitations of the Study and Suggestions for Future Research

During and after the study, the researcher found some limitations. The above multi-stage model can be tested in some other demographic areas to increase the generalisation. The data used to study the above model can be enlarged to the general public. Since ChatGPT is offering its services in India in the English language only, the sample was restricted to English language users only, which is very restricted and less in comparison to the original populations. As ChatGPT services are very new in India, users are very few in number, and their usage is also very limited. This study can also be further conducted in a longitudinal format to understand this adoption process more in detail, with some more antecedents to improve the model's predictability.

This study employed purposive sampling through personal & professional contacts and social media platforms, which may have probably introduced self-selection bias, as users with greater interest or exposure to ChatGPT were more likely to participate in the survey. Additionally, the study has some sampling limitations, as the sample consisted of a majority of young respondents and students, which can limit the generalizability of the findings to older users and non-student populations, whose perceptions and adoption process toward ChatGPT may differ. Future studies should therefore examine more diverse age groups and occupational backgrounds.

Consequently, the outcomes of the study should be interpreted with caution and should be used carefully to generalize to the adoption of other technology users. Future research should employ probability sampling or more diverse sampling strategies to capture the responses.

Although all hypothesized relationships were statistically supported, the findings should be interpreted with caution. Future research should replicate the proposed framework across different populations, contexts, and AI applications to examine the robustness and generalizability of the results, and it can also be executed on international students.

AUTHOR CONTRIBUTIONS

All authors contributed equally in this paper. Conceptualization was done by I.S. and A.S.; methodology was finalised by A.P. and A.S.; Data collection was done by S.P, H.G, A.P, A.S. software analysis was done by I.S., A.P, A.S. Findings and Analysis was discussed and finalised by I.S., A.S, A.P, S.P and H.G. writing was done by I.S and H.G review and editing were done by A.P and A.S. All authors have read and agreed to the published version of the manuscript.

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Formal ethical approval was not received, as there is no such committee at the university where study was undertaken. However, the study adhered to research ethical principles involving human respondents. Before completing the questionnaire, respondents were provided with an informed consent statement explaining the study's purpose, their voluntary participation, anonymity, confidentiality of their responses, and the right to withdraw from the survey at any time. Completion of the questionnaire was considered evidence of informed consent.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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