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Unveiling the Drivers of ChatGPT Adoption: A Meta-Analysis of Factors Influencing User Acceptance Across Diverse Contexts

Abstract

Purpose: This study investigates the primary factors influencing ChatGPT adoption by synthesizing findings from 30 empirical studies. It aims to develop a generalized framework explaining user acceptance across global contexts, offering insights for businesses and researchers concerned with AI technology integration, consumer behavior, and cross-cultural adoption trends.

Design/methodology/approach: A meta-analytical approach combining correlation metaanalysis, meta-analytic structural equation modeling (MASEM), and hierarchical metaregression was employed. Data from over 14,000 respondents across 16 countries were analyzed to test relationships grounded in the Technology Acceptance Model (TAM) and to examine the moderating effects of demographic, cultural, and national innovation indicators.

Findings: The results confirm significant positive effects of hedonic motivation, device credibility, and social influence on perceived usefulness and perceived ease of use. These perceptions are positively associated with user attitudes and behavioral intentions. Cultural dimensions, gender, and national innovation levels significantly moderate these relationships, offering actionable insights for tailoring AI adoption strategies across global markets.

Originality: This study presents the first comprehensive meta-analysis to propose a generalized, cross-cultural model of ChatGPT adoption. By integrating TAM with cultural and demographic moderators, it resolves inconsistencies in prior research and bridges theory and practice. The findings provide novel strategic implications for AI deployment across diverse industries and international consumer markets.

Keywords: artificial intelligence; ChatGPT adoption; meta-analysis; MASEM; hierarchical meta-regression.

1. Introduction

Artificial intelligence (AI) is revolutionizing human life, becoming an essential part of daily tasks and decision-making processes. Many companies now use AI to provide personalized recommendations (e.g., Netflix, Spotify), digital assistants and chatbots (e.g., Alexa, Siri), autonomous vehicles and navigation (e.g., Tesla, Uber), and healthcare diagnostics (e.g., IBM Watson Health). In line with these advancements, OpenAI introduced ChatGPT in late November 2022, marking a significant milestone in conversational AI. ChatGPT pushes the boundaries of human-machine interaction, demonstrating AI's potential in facilitating communication, supporting decision-making, and enhancing accessibility across industries. Reflecting its rapid success, by August 2024, ChatGPT reached over 200 million weekly users, double the number from 2023 (Reuters, 2024).

Following this trend in the "real world", businesses and IT academics have conducted numerous studies to better understand the factors associated with ChatGPT adoption. In this vein, several articles have been published in recent years across various contexts, such as education (e.g., Saif et al., 2024), retail (e.g., Niu et al., 2024), and hospitality (e.g., Ali et al., 2023). To understand the factors behind ChatGPT adoption, the Technology Acceptance Model (TAM) has been widely applied (e.g., Saif et al., 2024; Ma et al., 2024). TAM is a multidimensional framework consisting of external variables that impact two main internal dimensions: perceived usefulness (PU) and perceived ease of use (PEOU) (Davis, 1989). This model has been extensively studied in innovative business contexts because it relates to an individual's predisposition to adopt new technologies, such as ChatGPT (Venkatesh et al., 2008).

While these studies offer valuable insights into understanding ChatGPT adoption, several issues have also emerged. First, a wide variety of theoretical constructs have been tested as external variables, making it difficult to identify the main factors that explain ChatGPT adoption. Second, the studies lack generalizability since they often rely on cross-sectional research designs (e.g., Ma et al., 2023), non-random samples (e.g., Camilleri, 2024), and specific contexts (e.g., Saif et al., 2024). Third, different primary studies report varying effects for the same relationships. For example, while Saif et al. (2024) found a neutral effect of PEOU on the intention to adopt ChatGPT, Ma et al. (2024) reported a significant and consistent effect. Similar discrepancies are observed when analyzing the impact of PU on ChatGPT adoption. For example, Maheshwari (2023) argued that PU has no direct effect on ChatGPT adoption intentions, while Liu and Ma (2024) identified a strong positive influence. Given the mentioned issues, the current research was conducted to provide the following contributions. First, this meta-analysis-driven systematic review statistically synthesized key influential factors on ChatGPT adoption to provide generalized results and address conflicting findings from primary studies. Further, potential moderators were tested across a broad range that would otherwise be impossible in primary studies (Hulland & Houston, 2020). Many studies highlight the importance of exploring ChatGPT adoption across diverse cultural contexts, demographic groups, and regions, as most existing research is focused on specific locales or populations (e.g., Ma

& Ho, 2023; Camilleri, 2024; Niu et al., 2024). Therefore, several moderation analyses were conducted to investigate the potential influences of demographics (gender), cultural (Hofstede dimensions) characteristics, and study country origin (human development and innovation index) on the main direct effect of ChatGPT adoption.

From a managerial perspective, this research offers valuable insights for managers aiming to enhance user engagement. By understanding the key factors driving adoption, companies can tailor their strategies to better meet user needs and preferences, thereby improving the effectiveness of ChatGPT integrations. The generalized results provide managers with more reliable and comprehensive data, informing decision-making across different sectors and markets. These findings enable companies to anticipate user behavior, streamline adoption strategies, and confidently apply best practices, even in diverse and evolving environments. The analysis of cultural and demographic moderators can guide managers in refining their marketing strategies and user experiences to align with the specific characteristics of their target audiences, thereby increasing adoption rates across various demographic and cultural segments. Additionally, by accounting for the Human Development Index (HDI) and innovation index of the country of origin, the research sheds light on how ChatGPT adoption may differ across economic and innovation landscapes. Managers operating in international markets can leverage this information to adapt their strategies based on the technological maturity and innovation capacity of each market, optimizing resource allocation and strategic planning.

2. Theoretical Background and Research Framework

2.1 Technological Acceptance

The influence of digital social networks significantly impacts users' decisions when it comes to adopting new technologies (Graf-Vlachy et al., 2018). Many factors contribute to the acceptance of innovative tech, and the way it is perceived plays a crucial role (Sun & Zhang, 2006). Research on technology acceptance has been a popular focus since the 1990s, leading to various models and theories that analyze users' willingness to adopt new technologies.

The concept of "technology acceptance" was first introduced by Davis (1986). His work focused on how users' beliefs could affect their acceptance of technology, laying the groundwork for what is known as the Technology Acceptance Model (TAM). Davis's model was influenced by the Theory of Reasoned Action (TRA), which suggests that people's attitudes, shaped by their beliefs, drive their intentions and subsequent behavior toward technology use (Fishbein & Ajzen, 1975). TAM has been widely applied and validated across different fields, although certain limitations have led to various adaptations. As the model evolved, newer versions like TAM2, TAM3, and the Unified Theory of Acceptance and Use of Technology (UTAUT) were developed, incorporating additional factors to explain technology adoption more effectively (Venkatesh et al. 2003).

TAM2, introduced by Venkatesh and Davis (2000), expanded the original model by adding social and cognitive influences, recognizing the role of subjective perceptions, such as PU and social image. TAM3 further refined these factors, including variables like computer playfulness and anxiety (Venkatesh & Bala, 2008; Venkatesh et al., 2012). Several other adaptations, including those focused on specific technologies such as mobile learning, have added elements like perceived mobility value and user enjoyment. The UTAUT model, created by Venkatesh et al. (2003), unified these adaptations into a broader framework, later evolving into UTAUT2, which emphasized such consumer-centered factors as hedonic motivation and cost considerations.

Despite various new approaches and modifications, the constructs of PEOU and PU introduced by Davis remain central in understanding technology acceptance (Abdullah et al., 2016). PEOU relates to the user's perception of how easy the technology is to use, while PU focuses on the perceived benefits and efficiency gains from using the technology (Davis, 1996). Given the robust nature of TAM, it continues to be a key model for analyzing technology adoption trends in both academic and industry contexts.

Although TAM and its extensions provide a robust foundation for understanding technology adoption, recent research highlights that AI-based systems introduce unique psychological mechanisms that extend beyond traditional usability and usefulness considerations. In particular, AI-specific constructs such as algorithm aversion, AI anxiety, and human–AI trust have gained increasing scholarly attention. Algorithm aversion refers to users' tendency to distrust or avoid algorithmic recommendations after observing errors, even when algorithms outperform human decision-makers (Dietvorst et al., 2015). In parallel, AI anxiety captures feelings of discomfort, fear, or uncertainty when interacting with autonomous systems (Longoni et al., 2019). These concerns are especially salient in generative AI contexts, where outputs may appear human-like yet remain opaque in their underlying logic. Furthermore, human–AI trust extends beyond traditional system credibility by incorporating perceptions of fairness, transparency, explainability, and ethical integrity (Glikson & Woolley, 2020). Unlike earlier information systems, generative AI systems such as ChatGPT blur the boundary between tool and quasi-social agent, activating social-cognitive evaluations typically reserved for human interaction. Consequently, AI adoption may be influenced not only by PU and PEOU but also by deeper psychological responses related to control, autonomy, accountability, and perceived agency.

While our meta-analysis synthesizes the most consistently reported predictors in the emerging ChatGPT literature, we acknowledge that future theoretical development should further integrate AI-specific mechanisms to enrich existing technology acceptance models.

2.2 Research Framework of ChatGPT Adoption

Our research framework is based on a synthesis of prominent constructs examined in 30 primary studies related to ChatGPT adoption. The constructs illuminate customer perceptions of PEOU and PU, which, in turn, affect the outcomes (positive attitude and behavior intention). The proposed model (Figure 1) includes main and moderating effects, as delineated below.

Although the present framework centers on constructs most frequently examined in the primary studies, it is important to recognize that AI adoption may involve additional psychological mechanisms not yet consistently operationalized in the ChatGPT literature. Constructs such as perceived humanness, algorithm transparency, AI anxiety, and ethical concerns may represent important extensions to TAM in generative AI contexts. However, because these constructs were not sufficiently represented across studies to allow meta-analytic integration, they remain promising directions for future research.

2.2.1 Main Effects

Hedonic motivation refers to technology use driven by enjoyment, entertainment, and fun (Venkatesh et al., 2012). These aspects are widely recognized in the context of AI devices (e.g., Ma & Huo, 2023), as users often find pleasure in interacting with these systems (Abadie et al., 2024). In the case of ChatGPT, its hedonic qualities are evident through user interactions, offering experiences that evoke fun and entertainment. This is achieved, for example, through the instant gratification of immediate responses and the engaging, human-like conversational style. Numerous previous studies have examined the positive impact of hedonic motivation on PU and PEOU, consistently finding significant positive effects (e.g., Ma & Huo, 2023; Pham et al., 2024; Gulati et al., 2024).

Device credibility reflects the extent to which the outcomes provided by technological devices are perceived as trustworthy and accurate (Ali et al., 2023). The credibility of AI is reinforced when the system demonstrates strong problem-solving abilities and adapts effectively to user needs (Pham et al., 2024). In the case of ChatGPT, credibility can be evoked through various factors, such as delivering accurate and reliable information, maintaining professional and polished communication, ensuring consistency across interactions, and referencing sources or evidence. Consistent with this, previous research has identified credibility as a key antecedent of AI adoption, closely linked to both PU and PEOU (e.g., Ali et al., 2023; Tiwari et al., 2024).

Social influence in the technology field refers to the degree to which an individual perceives that important others believe they should adopt a new technology (Venkatesh et al., 2003). According to Venkatesh et al. (2003), social influence is a crucial factor in the adoption of new technology, particularly during its early stages of introduction. In the case of ChatGPT, several examples illustrate how social influence may be associated with higher adoption intentions, such as peer recommendations at work, endorsements from friends and family, influencer support, and viral social media trends. Following these practical examples, numerous studies have investigated the impact of social influence on ChatGPT adoption, with many findings indicating positive effects on PU and PEOU (Ma & Huo, 2023; Habibi et al., 2023).

PU and PEOU are key factors influencing customers' willingness to adopt technology (Silva et al., 2022). PU reflects the user's perception of how the AI device enhances their performance, while PEOU indicates how easy the system is to use (Granić & Marangunić, 2019). The perception of ChatGPT's usefulness can be evoked through various aspects, such as efficiency and time-saving, improved problem-solving, support for decision-making, and instant access to information. On the other hand, ChatGPT's ease of use is perceived through a seamless, intuitive, and user-friendly experience, including a simple interface, clear guidance and clarification, and the absence of any installation or setup requirements. Based on the TAM, we propose that both PU and PEOU are positively associated with users' attitudes, as perceptions of usefulness and ease of use provide greater insights into the performance of the AI service (Patel & Patel, 2018).

Positive user attitudes toward ChatGPT are a well-known and significant predictor of behavior intentions (e.g., Davis et al., 1986), as attitudes reflect users' overall evaluations of a product or service (Fishbein & Ajzen, 1975). In the case of ChatGPT, several factors can evoke positive attitudes, such as its user-friendly experience, the ability to simplify complex tasks, personalized interactions, and the instant gratification it provides. Previous research in the ChatGPT context has confirmed these assumptions, showing positive, significant, and consistent effects (e.g., Pham et al., 2024; Xu et al., 2024).

2.2.2 Moderation Effects

Demographic moderators: Following previous research (e.g., Foroughi et al., 2024; Camilleri, 2024), we examine the gender demographic moderator. Gender differences in technology adoption have been extensively examined in UTAUT and related frameworks (Venkatesh et al., 2003). Rather than assuming categorical differences, gender is conceptualized as a proxy for variations in risk sensitivity, performance orientation, and technology confidence. Prior research (e.g., Santini et al., 2026) suggests that men tend to emphasize instrumental performance gains, whereas women may exhibit higher sensitivity to uncertainty and trust-related concerns. In the context of AI systems such as ChatGPT, where algorithmic opacity and reliability may be salient, gender may moderate the extent to which positive attitudes translate into behavioral intentions. Thus, gender is examined as a boundary condition influencing the strength of the attitude–intention relationship rather than as a deterministic trait.

Cultural moderators: Previous research has highlighted the importance of cultural factors in understanding technology adoption (e.g., Foroughi et al., 2024; Camilleri, 2024; Ma & Hu, 2024). In this study, we applied Hofstede's six cultural dimensions based on the countries of origin of the participants: power distance, individualism, achievement orientation, uncertainty avoidance, long-term orientation, and indulgence orientation. Power distance reflects the extent to which inequalities in power and authority are accepted within a society (Hofstede, 1984). In low power-distance cultures, individuals are more likely to rely on personal evaluation rather than institutional authority when forming behavioral intentions. Venkatesh et al. (2003) demonstrate that social and structural factors influence technology acceptance differently across cultural contexts. Therefore, in societies where hierarchical authority is less emphasized, PU and device credibility may exert stronger direct effects on behavioral intention because adoption decisions are driven more by individual cognitive assessment than by normative structures. Individualism reflects the degree to which personal goals and autonomy are prioritized over group norms (Hofstede, 1984). Research suggests that individuals in highly individualistic cultures tend to emphasize personal performance gains and independent decision-making (Abbasi et al., 2015). Since PU represents performance enhancement (Davis, 1989), the PU on the behavioral intention relationship may be stronger in individualistic contexts where personal benefit maximization is central. Achievement orientation emphasizes competition, performance, and success (Hofstede, 1984). Cultures high in achievement orientation prioritize productivity and goal attainment. Because PU reflects task efficiency and performance improvement (Davis, 1989), it is theoretically consistent that performanceoriented cultures amplify the impact of usefulness perceptions on behavioral intention. This aligns with prior cross-cultural technology acceptance findings (Venkatesh et al., 2003).

Uncertainty avoidance refers to the degree to which societies feel uncomfortable with ambiguity and risk (Hofstede, 1984). Technologies such as ChatGPT involve algorithmic opacity and probabilistic outputs, which may heighten perceived uncertainty. In high uncertainty-avoidance cultures, adoption may depend more strongly on trust-related cues and credibility signals. Prior research suggests that tolerance for uncertainty influences openness to innovation (Abbasi et al., 2015), supporting the examination of uncertainty avoidance as a moderator. Long-term orientation reflects the extent to which societies prioritize future rewards, persistence, and pragmatic adaptation (Hofstede, 1984; 2001). Cultures high in longterm orientation are generally more adaptable to technological change and innovation. As suggested in cross-cultural technology research (Jan et al., 2022), such societies may demonstrate stronger relationships between PU and behavioral intention due to their futureoriented investment mindset. Finally, indulgence measures the degree to which societies emphasize enjoyment, gratification, and the pursuit of pleasure (Hofstede, 2001). ChatGPT provides instant responses, interactive engagement, and hedonic value. In indulgent cultures, immediate performance gains and experiential satisfaction may strengthen the translation of PU into behavioral intention. This interpretation aligns with cultural value theory (Hofstede, 2001) and prior cross-national findings in technology adoption contexts (Venkatesh et al., 2003).

While Hofstede’s dimensions provide a widely used and comparable cross-national framework, contemporary cultural research suggests that digital-age cultural variations may also be shaped by alternative value systems. For example, Schwartz’s cultural value theory emphasizes autonomy versus embeddedness and egalitarianism versus hierarchy, which may offer nuanced insights into AI adoption behaviors. Similarly, the GLOBE framework introduces dimensions such as institutional collectivism and performance orientation that may better capture organizational and technological readiness. In digitally connected societies, cultural differences may increasingly reflect attitudes toward technological disruption, innovation tolerance, and institutional trust rather than traditional value dimensions alone. Accordingly, future research should consider integrating multiple cultural frameworks to better understand AI adoption across rapidly evolving digital ecosystems.

Country characteristics studied: We examined two potential moderators related to countryspecific characteristics: the Human Development Index (HDI) and the Country Innovation Index (CII). High HDI countries are expected to have more advanced skills for online interactions, such as using tools like ChatGPT, which can lead to greater confidence and a higher likelihood of adopting new technologies (Kim & Peterson, 2017; Santini et al., 2019). The CII, published annually by the World Intellectual Property Organization (WIPO), is a comprehensive measure of a country's innovation capabilities. It is reasonable to assume that users in countries with a high CII are more familiar with new technologies and thus exhibit more favorable behavior toward adoption (Teo & Liu, 2007; Kim & Peterson, 2017). Figure 1 summarizes the research model, which was tested in the current meta-analysis. The relationships depicted are based on prominent connections identified in previous studies, with an emphasis on the TAM. The most frequently examined external variables include hedonic motivation, device credibility, and social influence, all of which impact PU and PEOU. These, in turn, influence users' positive attitudes toward ChatGPT, ultimately enhancing behavior intentions. Additionally, we have incorporated several moderators, categorized into demographic, cultural, and country-specific characteristics.

---- Insert here Figure 1 ----

3. Methods

We conducted our study following traditional meta-analysis methods (e.g., Santini et al., 2020; Ladeira et al., 2025; Ladeira et al., 2026a; Ladeira et al., 2026b). This approach involved three main steps: (1) search process and selection of valid articles, (2) coding process, and (3) analysis procedures. Each step used in this meta-analysis is detailed below.

3.1 Search and Select Valid Articles

To identify relevant studies for this meta-analysis, we conducted a search in the Scopus and Google Scholar databases. The following keywords linked to the article title and/or abstract: 'ChatGPT' and 'acceptance' OR 'use' OR 'adoption' OR 'determinants' OR 'antecedents' OR 'factors' were applied. The search was limited to the Business, Management, and Accounting fields, and only studies published in English were included. This initial search resulted in 293 potential articles, all of which were downloaded for further screening. Following established meta-analysis procedures (e.g., Babic-Rosario et al., 2016), we applied the following criteria to select valid studies: (1) The article must report valid statistics that can be converted to correlation (r), and (2) the article must provide effects related to ChatGPT adoption. Based on these criteria, 263 articles were excluded due to a lack of valid statistics (e.g., qualitative and/or theoretical studies) or because they were not focused on ChatGPT in particular, but on AI or information technology in general. Ultimately, 30 valid studies were identified, yielding a total of 96 effect sizes and a cumulative sample of 14,037 respondents.

3.2 Coding Process

After identifying the valid articles, we proceeded with the coding process. We extracted relevant information from each article for our meta-analysis. The following data were collected: study identification, author names, journal names, country of origin, sample size, construct names related to ChatGPT adoption, effect sizes, mean sample age, percentage of female participants, indices related to Hofstede's cultural dimensions, HDI, and CII. Before beginning the coding process, all authors discussed the coding details and developed a coding schema. The first two articles were coded by all authors to ensure consistency. Subsequently, one researcher conducted the initial coding, and another researcher reviewed all codifications, following the recommendations of Rust and Cooil (1994). The data accuracy rate was 95%. Any discrepancies were discussed among all authors to reach a consolidated understanding.

3.3 Analysis Procedures

Three analyses were conducted to investigate the proposed research framework, including (1) correlation meta-analysis, (2) meta-analytic structural equation modeling (MASEM), and (3) hierarchical meta-regression. Each analysis is detailed below.

Correlation meta-analysis. To provide an initial understanding of ChatGPT adoption, we conducted a correlation meta-analysis, following traditional meta-analysis methods (e.g., Kim & Peterson, 2017; Santini et al., 2019). The effect sizes were based on correlation coefficients. For studies that did not report r coefficients, we converted the available statistics (e.g., χ^2, F, t, z, β, and p-values) to correlations, following the procedures outlined by Hunter and Schmidt (2004). Effect sizes were adjusted for sample size (Hunter & Schmidt, 2004), and we applied a random-effects model to account for sample heterogeneity (Rosenthal, 1979). We set confidence intervals at 95% and assessed heterogeneity using Cochran's Q and I^2 statistics (Higgins et al., 2003). The analysis was performed using the 'metacor' function in the R package 'meta' (Viechtbauer, 2010).

MASEM. MASEM was employed to test the direct effects in our theoretical model, as it allows for the meta-analytic analysis of covariance structures using standard structural equation modeling estimation (Cheung, 2015). The model fit was assessed based on common guidelines for acceptable fit indices (i.e., CFI and TLI ≥ 0.90, RMSEA ≤ 0.08) (Cheung, 2015; Jak, 2015). All analyses were conducted in R Studio using the MetaSEM package (Cheung, 2015), OpenMx 2.0 (Neale et al., 2016), and the metafor package (Viechtbauer, 2010).

Hierarchical Meta-Regression. A hierarchical meta-regression was conducted to analyze the proposed moderators. The rma function from the R package metafor (Viechtbauer, 2010) was used to perform hierarchical meta-regression, accommodating both continuous and categorical moderators as well as covariates (Harrer et al., 2021).

4. Results

4.1 Descriptive Statistics

The results presented in Table 1 provide an overview of descriptive statistics on ChatGPT adoption antecedents. Through correlation meta-analysis, the effects of each variable synthesized from the finalized 30 articles on the intention to use ChatGPT were examined.

----- insert here Table 1 ------

As observed in Table 1, all relationships exhibited positive, significant, and consistent effect sizes. The strongest relationship was device credibility (r = .600), followed by positive attitude toward ChatGPT (r = .578), PU (r = .558), hedonic motivation (r = .524), social influence (r = .500), and PEOU (r = .489). Another notable finding is the consistency of these results. All Fail-Safe Numbers (FSN) were very high, exceeding 7,000. The FSN estimates the number of non-significant or unpublished studies needed to nullify the observed findings. Finally, we assessed publication bias using Egger's test (Egger et al., 1997), which measures funnel plot asymmetry based on the intercept from the regression of effect estimates on their standard errors. The Egger's test for all relationships tested was not significant, indicating no evidence of publication bias. Overall, these results rule out the possibility of publication bias.

Finally, it is important to note that the I^2 statistics indicate substantial heterogeneity across most relationships ($I^2 > 90\%$). While a random-effects model was employed to account for betweenstudy variability, these elevated heterogeneity levels also carry substantive implications. The variability likely reflects differences in national contexts, industry settings, sampling characteristics, and measurement operationalizations across the 30 primary studies. Given that ChatGPT adoption research spans diverse cultural and technological environments, such heterogeneity is theoretically expected. Therefore, rather than viewing I^2 solely as a statistical concern, it signals the importance of exploring contextual moderators, which we subsequently examine through hierarchical meta-regression.

4.2 Determinants of ChatGPT Adoption

To test the research model, we applied the MASEM. The results provided indices indicating a reasonably good model fit (CFI = .977; TLI = 931, and RMSEA = .02) (Hair et al. 2017).

---- insert here Table 2 ----

Table 2 presents the pooled meta-analytic correlation matrix among the main constructs related to ChatGPT adoption. The correlation structure presents a clear and consistent pattern that is in line with the Technology Acceptance Model (TAM). Strong positive correlations are observed between PU and attitude (r = .598), as well as between attitude and behavior intention (r = .570), indicating that users who perceive ChatGPT as useful tend to develop positive attitudes, which in turn increase their intention to use the system.

In addition, PEOU is strongly correlated with PU (r = .532), supporting the traditional TAM assumption that easier systems are perceived as more useful. The three external variables, i.e., hedonic motivation, device credibility, and social influence, show moderate to strong correlations with both PU and PEOU. This suggests that enjoyment, trust in the system, and opinions of others play an important role in shaping users' beliefs about ChatGPT. Furthermore, the correlations among the external variables themselves are moderate, indicating that these constructs are related but conceptually distinct. Overall, the correlation matrix demonstrates a theoretically coherent nomological network. It also provides empirical support for the proposed structural relationships tested in the MASEM presented in Table 3.

---- insert here Table 3 ----

As shown in Table 3, all effects are positive and significant. First, hedonic motivation has a positive effect on both PU (β =0.264) and PEOU (β = 0.237). The results indicate that users who find the experience enjoyable are more likely to find the system useful and easy to use. Second, device credibility positively influences PU (β = 0.286) and PEOU (β =0.266). This suggests that when users trust the device, they are more likely to perceive it as useful and easy to operate. Third, social influence presents a positive impact on PU (β = 0.226) and PEOU (β = 0.266). The findings indicate that the opinions of others can shape users' perceptions of both the utility and ease of use of the system. Fourth, ease of use positively impacts PU (β = 0.106) and attitudes (β = 0.393), so users who find the system easy to use tend to view it as more useful and develop a positive attitude toward it. Fifth, PU strongly influences attitudes (β =0.345) and behavior intention (β = 0.360). The results show that the perception of the system's usefulness is a key driver of both favorable attitudes and intentions to use it. Sixth, attitudes provide a strong impact on behavior intention (β = 0.431), so positive attitudes toward the system significantly increase the likelihood of behavior intentions. Finally, and in order to follow the traditional TAM proposed (Davis et al., 1986), we investigate the possible mediation effects of attitude toward PU and behavior intention. The results confirm the assumption and suggest that PU influences behavior intention through attitudes (β = 0.141), indicating an indirect effect. This highlights the importance of building a positive attitude to translate PU into actual behavior intentions.

4.3 Moderating Effects

To enhance the understanding of ChatGPT adoption, we conducted a hierarchical metaregression to examine several moderating effects. Model 1 included a demographic moderator (gender). Model 2 examined cultural moderators (power distance, achievement orientation, uncertainty avoidance, long-term orientation, and indulgence). Model 3 focused on countryspecific characteristics (HDI and CII). Table 4 summarizes the findings.

---- insert here Table 4 ----

As shown in Table 4, we identified several significant moderation effects. For demographic moderators, the analysis revealed that the male sample, compared to the female sample, strengthens the relationship between attitude and behavior intention ($\beta = -0.2587$; CI = -0.4978 to -0.0196; $p = 0.0340$).

Regarding cultural moderators, the findings indicate that studies conducted in contexts with low power distance (versus high) and high achievement orientation (versus low) exhibit stronger effects on device credibility ($\beta = -0.6849$; CI = -0.8940 to -0.4758; $p < 0.0001$; $\beta = 0.3108$; CI = 0.1125 to 0.5090; $p = 0.0021$, respectively) and PU ($\beta = -0.5063$; CI = -0.9757 to -0.0369; $p = 0.0345$; $\beta = 0.5872$; CI = 0.0157 to 1.1586; $p = 0.0440$, respectively) in relation to behavior intention.

Additionally, the cultural dimension of indulgence significantly moderates the effect of PU on behavior intention. In cultures with high levels of indulgence, the direct effect of PU on behavior intention is stronger ($\beta = 0.5346$; CI = 0.1367 to 0.9324; $p = 0.0085$) compared to cultures with low levels of indulgence.

5. Discussion

AI has revolutionized many aspects of our daily lives, with ChatGPT emerging as one of the most widely used AI tools by both businesses and consumers. In line with this trend, the academic community has shown growing interest, conducting numerous studies to identify the factors that influence consumer adoption of this technology. Research conducted across a diverse range of contexts, countries, and cultures has contributed significantly to the body of knowledge on this topic, though some discrepancies remain. In response to these inconsistencies, we conducted a meta-analysis that synthesized the results of 30 previous studies on ChatGPT adoption determinants, encompassing over 14,000 respondents across 16 different countries. This comprehensive analysis aims to provide a deeper understanding of the factors influencing ChatGPT adoption. Table 5 summarizes the key findings of this research.

---- insert here Table 5 ----

5.1 Theoretical Applications

This meta-analytical investigation makes significant contributions to understanding ChatGPT adoption. From a theoretical perspective, we offer the following insights: First, our research organizes and provides a comprehensive overview of ChatGPT adoption. Through the systematic review facilitated by the meta-analysis, we identified the most prominent constructs employed in past studies examining ChatGPT adoption and found that the TAM is the most frequently used framework to analyze this phenomenon. We also observed that hedonic motivation, device credibility, and social influence are the most prominent external factors examined for their impact on PEOU and PU.

Second, through a correlation meta-analysis, we address and help resolve previous inconsistencies in the ChatGPT adoption literature. Prior studies have reported conflicting results for several key relationships, such as the effects of PU and PEOU on behavior intentions. We found that these relationships are both significant and highly consistent (FSN > 50,000) (Table 1).

Third, using results derived from MASEM, we provide a generalizable framework for ChatGPT adoption. The findings confirm the impact of all external variables (hedonic motivation, device credibility, and social influence) on PEOU and PU, which in turn enhance positive attitudes and influence the intention to adopt ChatGPT. We also observed that PEOU affects PU and shapes user attitudes, acting as a mediator. These findings consolidate traditional theories tested in the adoption of other technologies (e.g., Venkatesh et al., 2012; Patel & Patel, 2018).

Fourth, our moderation analysis reveals several important insights for ChatGPT adoption theories: (a) Male samples, compared to female samples, strengthen the relationship between positive attitudes and behavior intentions; (b) individuals in cultures with lower inequality and high achievement orientation show stronger relationships between device credibility and the intention to adopt ChatGPT, as well as between PU and the intention to adopt ChatGPT; and (c) cultures with a high indulgence orientation tend to perceive the system as more useful, leading to a higher likelihood of adoption. The cultural moderation findings are theoretically consistent with Hofstede's (1984; 2001) framework, which posits that societal values shape cognitive evaluation processes. In line with cross-cultural technology acceptance research (Venkatesh et al., 2003; Abbasi et al., 2015; Jan et al., 2022), our results suggest that performance orientation, authority structures, and gratification tendencies influence how usefulness and credibility perceptions translate into adoption intentions. Thus, ChatGPT adoption mechanisms operate within broader socio-cultural value systems rather than as culturally invariant processes. Taken collectively, our study not only consolidates existing knowledge on ChatGPT adoption but also provides a deeper understanding of both direct and indirect relationships. These contributions serve as a springboard for future research, offering a foundation to further explore the dynamics of ChatGPT and other AI device adoptions.

5.2. Managerial Applications

The managerial implications of this study are directly grounded in the magnitude and consistency of the meta-analytic findings.

First, device credibility emerged as the strongest antecedent among external variables ($r = .600$) and significantly influenced both PU ($\beta = .286$) and PEOU ($\beta = .266$), indicating that trust and perceived reliability are central factors associated with ChatGPT adoption. Managers should therefore prioritize transparency, performance consistency, and accuracy in AI systems. An illustrative example of how credibility can be operationalized is Tesla's Autopilot system, which provides detailed safety reports, clear communication of system limitations, and realtime interface feedback to increase user trust (Lambert, 2024). Similar transparency mechanisms in generative AI may strengthen adoption intentions.

Second, hedonic motivation demonstrated a robust effect on PU ($\beta = .264$) and PEOU ($\beta = .237$), suggesting that adoption is associated not only with instrumental benefits but also with experiential engagement. Managers should design AI interfaces that are interactive, dynamic, and personalized. For example, Spotify's AI-enhanced recommendation system integrates conversational and adaptive features that make interaction enjoyable while simultaneously reinforcing perceived utility (Sandzer-Bell, 2024). In generative AI contexts, incorporating adaptive tone, personalized prompts, and engaging interaction styles may amplify both usefulness and ease perceptions.

Third, social influence significantly affected both PU ($\beta = .226$) and PEOU ($\beta = .266$), reinforcing the importance of normative endorsement during early-stage diffusion. Organizations can leverage influencer partnerships, professional testimonials, and peer advocacy to strengthen perceived legitimacy. Microsoft's rollout of Copilot illustrates this mechanism: By collaborating with widely recognized technology influencers and integrating the tool within familiar productivity ecosystems, Microsoft amplified social validation and accelerated adoption.

Fourth, PU was a primary direct driver of behavioral intention ($\beta = .360$) and also exerted an indirect effect via attitudes (indirect effect = .141), confirming that communicating clear performance gains is essential for adoption. Managers should demonstrate productivity improvements, decision-support capabilities, and time-saving advantages rather than relying solely on novelty framing. For instance, demonstrating measurable workflow efficiency improvements through case demonstrations or usage analytics can reinforce perceived value.

Fifth, cultural moderation results suggest that adoption mechanisms vary across contexts. The effect of PU on behavioral intention was stronger in high-achievement and high-indulgence cultures, implying that performance-based messaging may be particularly effective in competitive environments, whereas experiential and gratification-oriented framing may resonate more strongly in indulgent societies. International firms should therefore adapt positioning strategies according to local value orientations rather than adopting uniform global messaging.

Sixth, although our results indicate that gender moderates the relationship between attitudes and behavioral intentions, these findings should not be interpreted as rigid or deterministic differences between men and women. Rather, they suggest that user segments may differ in the extent to which positive attitudes translate into behavioral intentions. Managers should avoid one-size-fits-all strategies and instead adopt data-driven personalization approaches that account for heterogeneous user preferences. Rather than relying on categorical gender distinctions, organizations are encouraged to focus on individual-level characteristics such as prior technological experience, task orientation, perceived risk sensitivity, and trust propensity. Designing flexible interfaces, offering customizable features, and using behavioral analytics to identify user-specific needs may be more effective than tailoring strategies solely based on demographic categories.

Seventh, beyond managerial implications, our findings also carry important societal and policy implications. As ChatGPT and similar AI systems become increasingly embedded in education, public services, healthcare, and organizational decision-making, understanding the determinants of adoption is critical not only for firms but also for policymakers and regulatory bodies. The strong effects of device credibility and PU highlight the importance of transparency, reliability, and accountability in AI deployment. Policymakers should encourage the development of clear standards for AI explainability, ethical data governance, and performance disclosure to enhance public trust. Moreover, the moderating effects of cultural dimensions suggest that AI adoption policies may need to be context-sensitive, reflecting differences in societal values such as power distance and indulgence. Governments and public institutions could promote inclusive digital literacy programs and equitable access to AI tools, particularly in countries with varying levels of human development and innovation capacity. By fostering trust, digital competence, and responsible AI frameworks, policymakers can help ensure that AI adoption contributes to societal well-being rather than exacerbating existing inequalities.

6. Study Limitations and Future Avenues

This study has several limitations, which offer opportunities for future research. The first limitation concerns our framework model. It was not possible to include additional variables because previous primary studies did not provide sufficient cross-correlation effects to input into a correlation matrix, which is required for running MASEM (Cheung, 2022; Jak & Cheung, 2020; Jak et al., 2020). Future studies could address this gap by incorporating new variables (e.g., perceived humanness, perceived novelty) to facilitate meta-analyses testing extended models. Second, this meta-analysis only included quantitative data due to the metaanalytic approach relying on correlation statistics (Hunter & Schmidt, 2004). Future research could address this limitation by conducting a systematic review focusing solely on qualitative studies, providing deeper insights into the nuances of ChatGPT adoption. Third, alternative methodologies could be employed to better understand ChatGPT adoption. Future research could use experimental designs, utilizing devices like eye-tracking for capturing visual attention or electroencephalograms (EEG) and FaceReader for measuring emotional responses. These tools could be particularly useful in evaluating some of the moderators explored in this study. Fourth, although we examined several demographic, cultural, and country-level moderators, our cross-cultural conclusions must be interpreted with caution due to data limitations in the primary studies. A substantial number of moderator analyses could not be calculated because insufficient effect sizes were available for certain relationships (see Table 4). In particular, some cultural dimensions (e.g., uncertainty avoidance, long-term orientation, and indulgence in specific paths), as well as country-level indicators (HDI and CII), lacked the minimum number of observations required to conduct reliable meta-regression analyses. This constraint is inherent to emerging research domains such as ChatGPT adoption, where empirical studies are still limited and unevenly distributed across countries and cultural contexts. As a result, although we identified significant moderation effects for selected cultural dimensions (e.g., power distance, achievement orientation, and indulgence), our findings do not allow for comprehensive cross-cultural generalizations across all Hofstede dimensions. Future research should expand empirical investigations across more diverse national settings and report complete correlation matrices to enable more robust and comprehensive moderator testing. Such efforts will strengthen the external validity and cross-cultural generalizability of AI adoption frameworks. Fifth, few studies on ChatGPT adoption have investigated indirect effects. We hope our proposed theoretical model will inspire future research to explore different mediators, enriching the understanding of the underlying mechanisms driving ChatGPT adoption. Sixth, additionally, the substantial heterogeneity observed across studies highlights the contextual variability inherent in the emerging ChatGPT literature. Although we addressed this through random-effects modeling and moderator analyses, future research should continue to investigate additional sources of heterogeneity, including industry type, measurement differences, and user experience levels. A more fine-grained classification of study contexts may further clarify variance patterns in AI adoption research. Seventh, although Hofstede's cultural dimensions provide a widely used and comparable crossnational framework (Hofstede, 1984; 2001), their application in this study should be interpreted with caution. Hofstede indices are based on historically derived national averages and assume relative cultural stability over time. However, cultural values may evolve, particularly in rapidly digitalizing societies where exposure to global technologies such as ChatGPT may reshape norms related to authority, innovation, and uncertainty tolerance. Treating Hofstede scores as fixed national traits may therefore overlook within-country heterogeneity and temporal shifts in digital attitudes. Moreover, the use of country-level cultural indices to explain individual-level adoption behavior raises potential ecological fallacy concerns. While national cultural scores provide contextual insights, they do not necessarily reflect the specific value orientations of individual respondents within each study. This limitation is particularly relevant in AI adoption research, where digital literacy, technological exposure, and generational differences may vary substantially within the same country. Future research could address these concerns by incorporating individual-level cultural measures, longitudinal designs to capture cultural evolution in digital contexts, or alternative cultural frameworks (e.g., Schwartz, 1992; House et al., 2004) that may better capture contemporary digital-age variations.

Eighth, this study treats ChatGPT adoption as a relatively static phenomenon, synthesizing cross-sectional evidence collected during the early diffusion phase of generative AI. However, ChatGPT is a rapidly evolving technology characterized by continuous updates, expanding functionalities, and increasing institutional integration. As AI systems mature, user perceptions and adoption drivers may shift. For example, early adoption may be influenced more strongly by novelty, social influence, and curiosity-driven hedonic motivation, whereas later-stage adoption may depend more heavily on sustained performance, reliability, integration into workflows, and trust stability. Because most primary studies were conducted within a narrow temporal window shortly after ChatGPT's public release, the meta-analytic results may reflect early-adoption dynamics rather than stable long-term usage patterns. Future research should adopt longitudinal designs, compare early and mature usage phases, and examine whether the strength of

TAM-related relationships changes as generative AI technologies move from experimentation to institutionalized routine use.

Finally, although this study synthesizes dominant TAM-related constructs, the current ChatGPT literature has not yet systematically incorporated AI-specific mechanisms such as algorithm aversion, AI anxiety, perceived autonomy, or ethical concerns. As generative AI technologies continue to evolve, future meta-analytic research may be able to integrate these constructs once a sufficient empirical base emerges.

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Figure 1. Structural Model of ChatGPT Adoption Examined in the Meta-Analysis

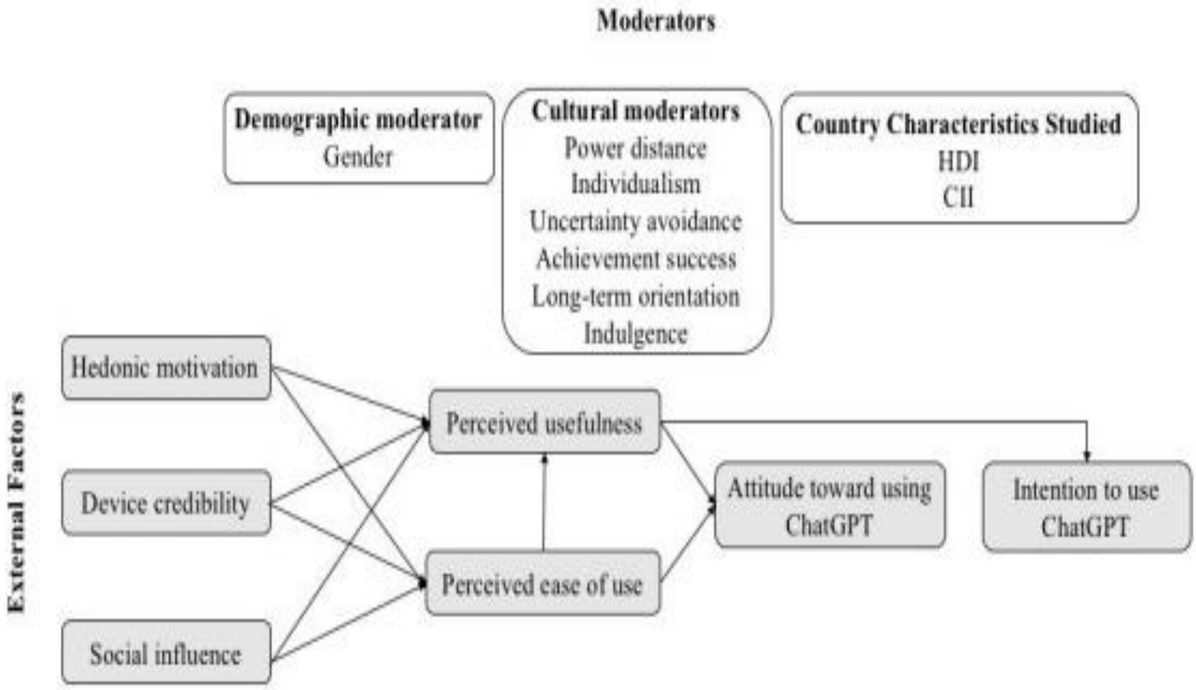

Table 1. Descriptive statistics of ChatGPT adoption antecedents

Variables	O	N	r	CI (95%)		Q	I^2	FNS	Egger's
Hedonic motivation	13	6814	.524	.455	.586	167.74*	92.8%	17132	.227
Device credibility	12	4869	.600	.471	.704	442.07*	97.5%	31621	.316
Social influence	9	4755	.500	.403	.586	141.28*	94.3%	7177	.421
Perceived usefulness	29	13430	.558	.495	.615	725.54*	96.1%	109149	.456
Perceived ease of use	23	11750	.489	.410	.560	635.48*	95.5%	51990	.053
Attitude toward ChatGPT	10	4172	.578	.497	.650	122.40*	92.6%	12439	.771

Note: O = number of observations taken from the analysis of the studies; N = number of accumulated samples of the assessed studies; r = correlation found in the studies correctly by sample size; CI (95%) = confidence interval; Q = test of heterogeneity at the individual; I^2 = scale-free index of heterogeneity; (*) = $p < .01$; ns = not significant; FNS = fail-safe N; Egger's = asymmetry test.

Table 2. Correlation matrix of ChatGPT adoption antecedents

	Hedonic motivation	Device credibility	Social influence	Perceived usefulness	Perceived ease of use	Attitud e	Behavior intention
Hedonic motivation							
Device credibility	.476						
Social influence	.484	.522					
Perceived usefulness	.550	.488	.546				
Perceived ease of use	.538	.541	.467	.532			
Attitude	.438	.466	.565	.598	.424		
Behavior intention	.509	.575	.485	.539	.472	.570	

Notes: Number of effect sizes: Hedonic motivation → device credibility (4); social influence (6); perceived usefulness (11); perceived ease of use (10); attitude (4); behavior intention (12). Device credibility → social influence (3); perceived usefulness (9); perceived ease of use (6); attitude (4); behavior intention (9). Social influence → perceived usefulness (9); perceived ease of use (7); attitude (3); behavior intention (10). Perceived usefulness → perceived ease of use (17); attitude (14); behavior intention (29). Perceived ease of use → attitude (9); behavior intention (23). Attitude → behavior intention (10).

Table 3. MASEM results

Direct effects			**β**
Hedonic motivation	→	Perceived usefulness	.264*
Device credibility	→	Perceived usefulness	.286*
Social influence	→	Perceived usefulness	.226*
Hedonic motivation	→	Perceived ease of use	.237*
Device credibility	→	Perceived ease of use	.266*
Social influence	→	Perceived ease of use	.266*
Perceived ease of use	→	Perceived usefulness	.106*
Perceived usefulness	→	Attitudes	.345*
Perceived ease of use	→	Attitudes	.393*
Perceived usefulness	→	Behavior intention	.360*
Attitudes	→	Behavior intention	.431*

Mediation effects

Predictor	**Mediator**	**Outcome**	**b**
Perceived usefulness			
	→		
	Attitudes		
	→		
		Behavior intention	
			.141*

Note: (*) p < .05.

Table 4. Hierarchical meta-regression of moderating effects

Model	Moderator	Coefficient	Standard Error	t-value	p-value	Confidence Interval (Lower, Upper)
		Hedonic Motivation and Behavior Intention				
Model 1	Gender	-0.1259	0.0940	-1.3401	0.1802	(-0.3101, 0.0583)
Model 2	Power distance	-0.0614	0.2858	-0.2150	0.8298	(-0.6216, 0.4987)
	Individualism	0.0653	0.1094	0.5963	0.5510	(-0.1493, 0.2798)
	Achievement orientation	0.1553	0.4355	0.3566	0.7214	(-0.6983, 1.0090)
	Uncertainty avoidance	-0.1554	0.3275	-0.4746	0.6351	(-0.7973, 0.4865)
	Long term orientation	0.2172	0.3260	0.6663	0.5052	(-0.4217, 0.8562)
	Indulgence	Not calculated (insufficient data)				
Model 3	HDI	0.0583	0.1159	0.5034	0.6147	(-0.1688, 0.2854)
	CII	-0.0538	0.1185	-0.4542	0.6497	(-0.2861, 0.1784)
		Device Credibility and Behavior Intention				
Model 1	Gender	0.1091	0.1863	0.5855	0.5582	(-0.2560, 0.4742)
Model 2	Power distance	-0.6849	0.1067	-6.4194	<.0001	(-0.8940, -0.4758)
	Individualism	-0.2080	0.364	-0.5713	0.5678	(-0.9216, 0.5056)
	Achievement orientation	0.3108	0.1012	3.0719	0.0021	(0.1125, 0.5090)
	Uncertainty avoidance	Not calculated (insufficient data)				
	Long term orientation	Not calculated (insufficient data)				
	Indulgence	Not calculated (insufficient data)				
Model 3	HDI	-0.0340	0.5493	-0.0619	0.9507	(-1.1106, 1.0426)
	CII	0.1740	0.5317	0.3273	0.7434	(-0.8680, 1.2160)
		Social Influence and Behavior Intention				
Model 1	Gender	-0.1661	0.1172	-1.4163	0.1567	(-0.3959, 0.0637)
Model 2	Not calculated (insufficient data)					
Model 3	HDI	-0.1074	0.1877	-0.5720	0.5673	(-0.4752, 0.2605)
	CII	-0.0648	0.2432	-0.2663	0.7900	(-0.5415, 0.4119)
		Perceived Usefulness and Behavior Intention				
Model 1	Gender	0.0528	0.0931	0.5670	0.5707	(-0.1297, 0.2353)
Model 2	Power distance	-0.5063	0.2395	-2.1139	0.0345	(-0.9757, -0.0369)
	Individualism	-0.0761	0.1109	-0.6867	0.4922	(-0.2934, 0.1412)
	Achievement orientation	0.5872	0.2916	2.0139	0.0440	(0.0157, 1.1586)
	Uncertainty avoidance	-0.1307	0.1759	-0.7429	0.4575	(-0.4754, 0.2141)
	Long term orientation	-0.2244	0.1807	-1.2413	0.2145	(-0.5786, 0.1299)
	Indulgence	0.5346	0.2030	2.6333	0.0085	(0.1367, 0.9324)
Model 3	HDI	-0.0487	0.1528	-0.3187	0.7500	(-0.3483, 0.2509)
	CII	0.0031	0.1452	0.0215	0.9829	(-0.2814, 0.2877)
		Perceived Ease of Use and Behavior Intention				
Model 1	Gender	0.0486	0.1049	0.4636	0.6429	(-0.1570, 0.2543)
Model 2	Power distance	0.1251	0.5846	0.2140	0.8305	(-1.0207, 1.2710)
	Individualism	-0.0037	0.0043	-0.8765	0.3808	(-0.0121, 0.0046)
	Achievement orientation	Not calculated (insufficient data)				
	Uncertainty avoidance	0.0874	0.4130	0.2116	0.8324	(-0.7221, 0.8968)
	Long term orientation	-0.1174	0.4151	-0.2829	0.7773	(-0.9309, 0.6961)
	Indulgence	0.0281	0.4768	0.0589	0.9530	(-0.9065, 0.9626)
Model 3	HDI	-0.0411	0.1788	-0.2298	0.8183	(-0.3915, 0.3093)
	CII	0.0309	0.2118	0.1458	0.8841	(-0.3842, 0.4459)
		Attitude and Behavior Intention				
Model 1	Gender	-0.2587	0.1220	-2.1206	0.0340	(-0.4978; -0.0196)
Model 2	Not calculated (insufficient data)					
Model 3	HDI	0.1988	0.1525	1.3040	0.1922	(-0.1000, 0.4976)
	CII	0.0897	0.1829	0.4908	0.6236	(-0.2686, 0.4481)

Table 5. Study findings, theoretical contributions, and managerial impacts

Study main findings	Theoretical contributions	Managerial impacts
Hedonic motivation significantly enhances perceived usefulness and ease of use.	The findings reinforce the TAM; draws from Venkatesh et al. (2012) on hedonic motivation's impact.	The results emphasize user engagement through entertaining and interactive features, such as personalized content or gamification.
Device credibility positively influences perceived usefulness and ease of use.	The findings reinforce the TAM and its extended versions (e.g., UTAUT), supporting the conclusions of Ali et al. (2023), who identified credibility as a key factor influencing technology adoption.	The results suggest that enhancing user trust through improved system transparency and the provision of accurate information will positively impact the perception of reliability.
Social influence impacts perceived usefulness and ease of use, affecting behavior intentions.	The results highlight the role of social dynamics in technology adoption (Venkatesh et al., 2003).	These findings confirm the importance of using peer recommendations and influencer marketing to boost adoption, particularly during the initial rollout phase of a new technology.
Perceived ease of use influences perceived usefulness and shapes user attitudes, acting as a mediator.	The findings reinforce the mediation analysis within TAM, supported by Davis (1989) and Patel and Patel (2018), showing the role of ease of use.	The results suggest that managers should simplify user interfaces and incorporate intuitive design elements to enhance the user experience and foster positive attitudes.
Cultural factors, such as power distance, achievement success, and indulgence, significantly moderate the adoption of ChatGPT.	The results highlight the connection between cultural traits and technology adoption behavior (Hofstede, 1984).	The findings suggest that managers should tailor marketing strategies according to cultural dimensions.
Gender significantly moderates the relationship between positive attitudes and behavior intentions, with stronger effects observed in male samples.	The findings are aligned with the UTAUT model's focus on demographic moderators (Venkatesh & Morris, 2000); highlights gender differences in technology adoption, suggesting men are more influenced by perceived usefulness in shaping behavior intentions.	Findings highlight functionality and efficiency for male users, and emphasize ease of use, support, and trust-building for female users.