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ChatGPT Behaviours among Nepalese Users:
An Application of Hedonic Motivation System Adoption Model

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Abstract

Drawing from Hedonic Motivation System Adoption Model (HMSAM), this paper purposes to investigate factors influencing ChatGPT adoption behaviour among Nepalese users. The paper utilised a cross-sectional survey research design to gather data from 350 users of ChatGPT in Nepal. The researchers employed purposive sampling to select respondents for the paper. To test hypotheses, this paper applied the Partial Least Squares Structural Equation Modelling (PLS-SEM) technique. This paper found that Joy and Perceived Usefulness (PU) have a significant influence on Behaviour Intention (BI). Perceived Ease of Use (PEOU) on Confirmation (CON) and Joy. Likewise, PEOU has a significant influence on Control (CON) and Joy. However, CON, curiosity (CU) and Joy do not significantly influence Immersion (IMM). CU does not influence BI and IMM, and PEOU does not influence CU and Perceived Usefulness (PU) among Nepalese ChatGPT users. This paper offers a significant outlook for the developers of ChatGPT to focus on the ease of using and joyfulness of using ChatGPT.

INTRODUCTION AND STUDY OBJECTIVES

In the advancement of different Artificial Intelligence (AI) fields, particularly in natural language processing, pattern recognition, and deep learning, the different industries such as healthcare, finance, education, and manufacturing have been impacted. Most recently, AI has gained more popularity with the launch of ChatGPT. The development of ChatGPT signifies profound achievement in the natural language processing of AI (Lund et al., 2023). The capability of ChatGPT has questioned the existing education system and wiped out many existing jobs. Because of the critical role of ChatGPT, it has become paramount to investigate the ChatGPT behaviours. Some users

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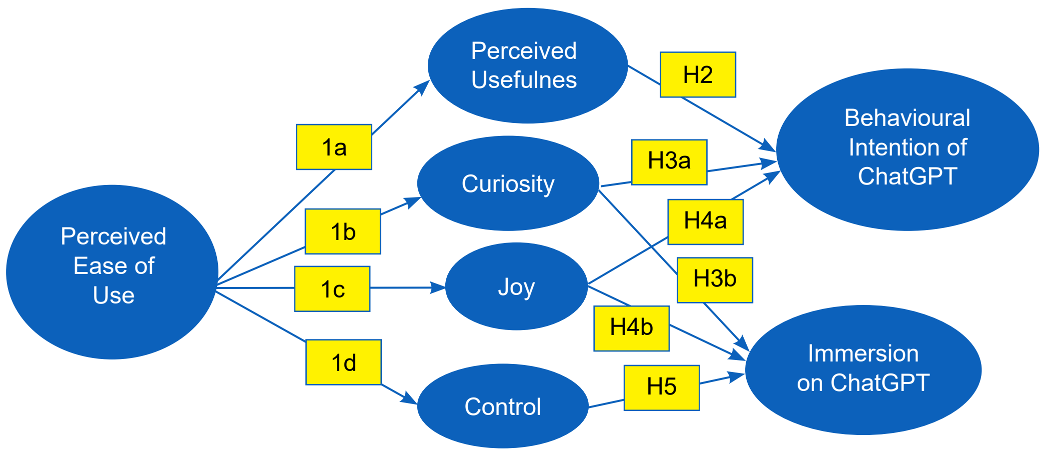
have shared that ChatGPT produces biased, inappropriate, or inaccurate content due to training data biases or user inputs. Gaining insights into these issues is crucial for responsible AI usage (Pappas et al., 2023). Furthermore, comprehending user behaviour helps enhance the user experience and tailor model responses. Understanding ChatGPT users' behaviours ensure responsible and effective utilisation of this powerful AI tool. Thus, ChatGPT usage behaviours should be critically investigated to unveil this enigmatic behaviour.

ChatGPT adoption behaviour can be investigated by applying different theoretical frameworks such as the Theory of Planned Behaviour (TPB), Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), and Hedonic Motivation System Adoption Model (HMSAM). van der Heijden (2004) documented that HMSAM holds particular relevance as it highlights the significance of hedonic motivation, emphasising the pleasure and enjoyment users derive from technology (van der Heijden, 2004). The HMSAM helps us understands why people adopt and use fun and enjoyable technologies like online games, social media, and digital music. It's different from the standard technology acceptance model (TAM) because HMSAM considers a more complex idea of cognitive absorption, which includes things like joy, control, curiosity, focus, and feeling like you're in a different world. Several studies have applied HMSAM to investigate adoption behaviours such as TikTok users in higher education (Deng &Yu, 2023); virtual reality games (Kari & Kosa, 2023); gamified learning environments (Oluwajana et al., 2018). Despite the plethora of literature on HMSAM, to the best of researchers' knowledge, HMSAM has not investigated ChatGPT adoption behaviours. This paper argues that ChatGPT users could engage with the AI system due to the enjoyment they experience during interactions, including engaging conversations and entertaining responses. Therefore, it is deemed appropriate to investigate ChatGPT adoption behaviours applying HMSAM.

Nepal's recent surge in ChatGPT usage, ranking second globally on Google search, is driven by its tech-savvy population, expanded internet access, and rising AI interest (Nepalitelecom, 2023). This growing interest reflects a broader enthusiasm for AI's potential to reshape sectors such as healthcare, education, and agriculture, emphasising the importance of ethical AI usage for equitable benefits. Despite the extensive usage of ChatGPT, the issue of ChatGPT adoption has received limited attention in Nepali research. Ojha (2023) reported that ChatGPT could be used for the improvement of information access, and employment prospects while acknowledging concerns about exacerbating the digital divide. However, scholarly investigations are paucity in the Nepali context. Pokhrel (2022) investigated the technology acceptance model to understand social media adoption intention among business school students. Despite the literature



Adopted form: (Lowry et al., 2013)
Figure 1. *Conceptual Framework*

on technology adoption, the adoption of ChatGPT has remained an unexplored area in Nepalese Context. Therefore, this paper intends to investigate factors influencing the adoption of ChatGPT among Nepalese users by utilising HMSAM.

LITERATURE REVIEW

The following paragraphs present the literature review.

Hedonic Motivation System Adoption Model (HMSAM)

The HMSAM is a conceptual framework introduced by Venkatesh and Brown (2001). This model focuses on the adoption of technology from the perspective of users' hedonic motivations, emphasising factors related to pleasure, enjoyment, and emotional satisfaction. HMSAM builds upon van der Heijden (2004) model of hedonic system adoption, incorporating cognitive absorption as a pivotal mediator between perceived ease of use and the behavioural intention to use hedonic motivation systems (See figure 1).

Relationship between Perceived Ease of Use and Control

Perceived Ease of Use (PEU) refers to an individual's belief in the effortlessness of using a specific technology (Davis, 1989). PEU refers to the extent to which users believe that interacting with ChatGPT, a specific technology in this case, requires minimal effort and is effortless. Likewise, Perceived Usefulness (PU) refers to an individual's belief in how a specific technology can enhance their job performance (Davis, 1989). It denotes to a user's belief in how ChatGPT can improve their job performance by enhancing work efficiency, productivity, and related tasks. Moreover, Control refers to the user's perception of being in charge of the interaction (Agarwal & Karahanna, 2000, as cited in Lowry et al., 2013). It denotes users' perception of ChatGPT users' ability to influence and guide the interaction, giving users a sense of authority and autonomy in shaping their engagement with the ChatGPT system. Furthermore, curiosity refers to the extent the experience arouses an individual's sensory and cognitive curiosity (Agarwal & Karahanna, 2000, as cited in Lowry et al., 2013). It states to how engaging with ChatGPT stimulates users' sensory interest (e.g., through intriguing responses and visuals) and intellectual interest (e.g., prompting questions, exploration, and critical thinking), motivating users to interact more actively with ChatGPT. Finally, Joy refers to the pleasurable aspects of interactions described as being enjoyable rather than boring (Agarwal & Karahanna, 2000, as cited in Lowry et al., 2013). It refers to the pleasure and enjoyment users derive from their interactions with ChatGPT, characterised by feelings of delight and satisfaction, as opposed to finding the interactions dull or uninteresting.

Lowry et al. (2013) in HMSAM illustrated that PEOU has a significant influence on PU, CU, Joy, and CON. It indicated that ease of use of technology could be instrumental in the usefulness of technology, curiosity for using technology, joy for using it, and control of the technology they are using. Many previous studies have documented that PEOU has a significant influence on PU (e.g., Davis, 1989; Pokhrel, 2022); Curiosity, Joy and Control (e.g., Deng & Yu, 2023; Huda et al., 2020; Kari & Kosa, 2023; Oluwajana et al., 2018). It refers to the ease of using technology that can develop curiosity, joy, and control over using technology such as ChatGPT. Based on the argument, the paper hypothesised that:

H1a : Perceived Ease of Use positively influences Perceived Usefulness of ChatGPT usage.

H1b : Perceived Ease of Use positively influences Curiosity of ChatGPT usage.

H1c : Perceived Ease of Use positively influences Joy of ChatGPT usage.

H1d : Perceived Ease of Use positively influences Control of ChatGPT usage.

Perceived Usefulness and Behaviour Intention of ChatGPT

Behavioural Intention (BI) refers to an individual's expressed willingness or plan to perform a specific behaviour in the future (Meyerhoff, 2007). BI implies to an individual's commitment and determination to undertake specific actions during their interactions with ChatGPT. Extensive research, supported by models like HMSAM (Lowry et al., 2013), van der Heijden (2004) and TAM (Davis, 1989), consistently demonstrates a positive relationship between PU and BI to adopt technology, a finding evident in diverse contexts such as TikTok for education (Deng & Yu, 2023), virtual reality gaming (Kari & Kosa, 2023), and adopting a healthier diet (Chan et al., 2021). Even in Nepal, Pokhrel (2022) PU significantly influences social media adoption among undergraduate students. Building on this, this paper hypothesised that:

H2 : Perceived Usefulness positively influences Behaviour Intention of ChatGPT usage.

Relationship between Curiosity, Behavioural Intention and Immersion

Immersion refers to the experience of total engagement in which other attentional demands are, in essence, ignored (Agarwal & Karahanna, 2000 as cited in Lowry et al., 2013). It denotes to users being fully engaged and absorbed in their interactions with the AI system, to the point where they ignore or overlook other distractions or demands. Previous studies, exemplified by Lowry et al. (2013), consistently establish that CU significantly influences BI and IMM. This pattern is supported by studies such as Deng and Yu (2023), Kari and Kosa (2023), and Oluwajana et al. (2018), which all emphasise the pivotal role of curiosity in driving BI and IMM across various domains. Nevertheless, Huda et al. (2020) and Chan et al. (2021) found exceptions in which curiosity did not notably impact satisfaction or intention. The result implies that ChatGPT stimulated users' sensory interest and motivation to interact more actively with ChatGPT improving the intention of using it and immersing with it. Based on the argument, the following hypotheses were developed:

H3a : Curiosity positively influences Behaviour Intention of ChatGPT usage.

H3b : Curiosity positively influences Immersion of ChatGPT usage.

Relationship between Joy, Behavioural Intention and Immersion

The HMSAM and Van der Heijden's Model consistently highlight the significant role of Joy on Behaviour Intention and Immersion in technology usage (Lowry et al., 2013; van der Heijden, 2004). Several studies documented that Joy has a significant influence on Behaviour Intention and Immersion. Deng and Yu (2023) found that Joy influenced Chinese TikTok users' intention for educational use. Kari and Kosa (2023) emphasised Joy's impact on the intention to engage in virtual reality games. Oluwajana et al. (2019) demonstrated the link between joy and gamified learning platform adoption among students. Hunda et al. (2020) established joy's influence on user satisfaction with video-on-demand applications. Finally, Oluwajana et al. (2019) study reinforced this relationship in gamified learning platforms among students. These findings collectively indicate that joy enhances immersion, motivating individuals to engage more actively in their respective contexts. Based on the argument and pieces of evidence, the researchers assume that the Joyful users of ChatGPT could intend to use ChatGPT and Immerse with their usage. Thus, it is hypothesised:

H4a : Joy positively influences Behaviour Intention of ChatGPT usage.

H4b : Joy positively influences Immersion of ChatGPT usage.

Relationship between Control and Immersion on ChatGPT

Relationship between Control (CON) and Immersion (IMM)

Previous research, such as Lowry et al. (2013) work, has consistently shown that users' perceived CON over interactions with technology significantly impacts their IMM, leading to a more satisfying experience and increased utility across domains. For instance, Deng and Yu (2023) found that control influenced Chinese TikTok users' immersion in educational contexts, while Kari and Kosa (2023) demonstrated a similar effect in virtual reality games, suggesting that control enhances engagement. Oluwajana et al. (2019) study on gamified learning platforms among students further supports this relationship, emphasising that control fosters immersion. Building upon the HMSAM, the researchers assume that users' sense of control during ChatGPT interactions leads to immersion.

H5 : Control positively influences Immersion of ChatGPT usage.

RESEARCH METHODS

This section presents research design, population and sample, measures and data collection and analysis procedures.

Research Design

This paper employed a cross-sectional survey research design to gather data from 350 users of ChatGPT in Nepal. Given the paper's objective of investigating the factors that influence ChatGPT usage, the cross-sectional survey design was chosen as the most suitable technique.

Population and Sample

To increase the representativeness of ChatGPT users, this paper targeted a population of ChatGPT users throughout Nepal. The paper has selected all seven provinces in which ChatGPT users were contacted and requested to participate in the paper. Likewise, this paper applied a purpose sampling technique to reach ChatGPT users. The paper applied the purposive sampling technique as it allows researchers to deeply engage in the data collection process (Subedi et al., 2023). Moreover, following the sample size recommendation of Hair et al. (2016), the paper collected data from 350 Nepalese ChatGPT users. The sample size was further classified into Koshi Province (50), Madhesh Province (100), Bagmati Province (150), Gandaki Province (50), Lumbini Province (50), Karnali Province (50), Sudurapashchim Province (50). Researchers assumed that this classification of sample would represent the population because of the homogenous nature of ChatGPT users.

Measures

To capture the ChatGPT usage, this paper has applied HMSAM ~~of~~ developed by Lorry et al. (2013). To accurately measure behaviour intention, immersion, perceived ease of use, perceived usefulness, curiosity, joy, and control variables by adapting 34 items. All items were anchored in a 5-point Likert Scale.

Data Collection and Analysis procedure

The adapted questionnaires were pilot tested to ensure the readability of the question, face validity, and reliability. The pilot test was conducted among 60 ChatGPT users studying MBA, BBA, and BHM at different colleges in Kathmandu Valley. Based on the feedback provided and Cronbach alpha values higher than 0.60, the full-scale survey was administered from 25th March 2023 to 10th June 2023. Out of 500 distributed printed questionnaires, 450 responses were returned. For Madhesh Province and Bagmati Province, researchers collected data from ChatGPT users. In other remaining provinces, researchers approached respondents with different colleges in which they were studying. Hundred unengaged and missing responses were eliminated during data cleaning. The final 350 responses were analysed by applying Statistical Packages for Social Sciences (SPSS) and Smart PLS (Partial Least Square) 4.0.

Data Analysis and Discussion

The demographic profile of 350 respondents is described in terms of age, gender, level of education, occupation, User frequency of ChatGPT, ChatGPT using duration of users, and user province. The majority of respondents were female (n=192, 54.9 percent). The results indicate that the most frequent respondent category held a bachelor's degree qualification (n=220, 62.9-percent). Among the respondents, the largest portion (n=137, 39.1 percent) hailed from the Bagmati province. Similarly, a significant number of respondents (n=147, 42—percent) reported habitual usage of ChatGPT at least once a week. Lastly, the highest count of respondents (n=141, 40.3 percent) had been habitually using ChatGPT for less than one month.

Common Method Biases

In this study, the paper employed Harman's single-factor analysis to assess whether a single factor could adequately clarify the observed variations. The results revealed that an unrotated single factor explained only 12.12 percent of the variance, falling significantly short of the recommended threshold of 50 percent as suggested by Podsakoff et al. (2003). Consequently, the researchers can reasonably conclude that the dataset does not exhibit signs of common method biases.

Structure Equation Model (SEM)

Structural Equation Modelling (SEM) stands as a highly valuable research methodology, primarily due to its ability to capture latent variables, address various forms of measurement errors, and evaluate comprehensive hypotheses (Henseler et al., 2016). SEM encompasses two primary approaches: Covariance-based SEM (CB-SEM) and Variance-based SEM (PLS-SEM). While dealing with multiple variables and intricate interconnections among constructs, as emphasised by Hair et al. (2021), PLS-SEM emerges as the preferred choice. Consequently, PLS-SEM, which seamlessly combines measurement and path modelling, is considered especially well-suited for researchers.

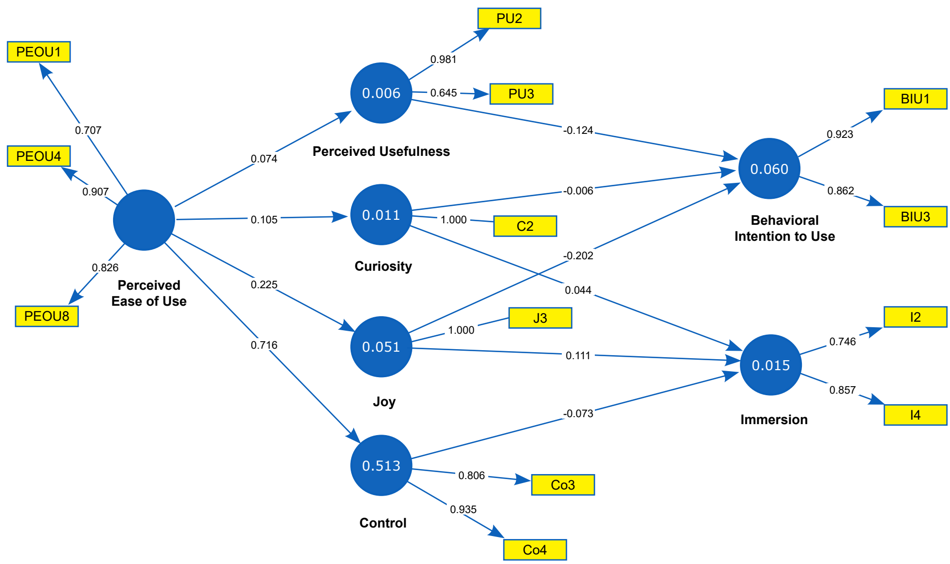


Figure 2. *Measurement Model*

Measurement Model

To estimate measurement model, researchers have employed reliability and validity techniques (Bido et al., 2014). To establish reliability, two widely utilised techniques, Cronbach Alpha (CA) and Composite Reliability (CR), were utilised. Notably, both CA and CR values exceeded the threshold of 0.744, affirming the reliability of the measurement model (Hair et al., 2011), as indicated in Table 1. Moreover, in terms of Convergent Validity, the analysis incorporated Average Variance Extracted (AVE) statistics, which exhibited values ranging from 0.645 to 0.798 across the constructs. These values comfortably exceeded the recommended threshold of 0.50 (Fornell & Larcker, 1981), thus indicating the presence of convergent validity. Due to the poor factor loadings of Perceived Ease of Use (PEU), Perceived Usefulness (PU), Confirmation (CON), and Immersion (IMM) were dropped from the measurement model (see Table 1). Most importantly, Joy and Curiosity retained only 1 item, showing serious issues in measurement model (Bido et al., 2014).

Discriminant Validity

Discriminant validity in this paper was assessed using the criteria outlined by Fornell and Larcker (1981) and the Heterotrait-Monotrait Ratio (HTMT). When the square root of a construct's Average Variance Extracted (AVE) exceeds its correlation with all other constructs, it indicates the presence of discriminant validity. In our analysis, the paper found that the square roots of AVEs consistently exceeded the correlations with other constructs, as indicated in Table 2. Furthermore, Teo et al. (2008) recommend a threshold of 0.90 or less for discriminant validity. In

Table 1
Reliability and Validity of Model

Constructs	Indicators	Outer Loadings	Alpha	CR (rho_a)	CR (rho_c)	AVE
	PEOU1	0.707				
	PEOU4	0.907				
Perceived Ease of Use	PEOU8	0.826	0.749	0.793	0.857	0.668
	PU2	0.981				
Perceived Usefulness	PU3	0.645	0.652	1.642	0.809	0.689
Curiosity	CU2	1				
	CON3	0.806				
Confirmation	CON4	0.935	0.705	0.835	0.864	0.762
	IMM2	0.746				
Immersion	IMM4	0.857	0.457	0.475	0.784	0.645
	BI1	0.923				
Behaviour Intention	BI3	0.862	0.752	0.792	0.888	0.798
Joy	Joy3	1				

Note. Based on authors' calculation

Table 2.
Discriminant Validity (Fornell and Larcker's Criterion and HTMT Ratios)

Constructs	1	2	3	4	5	6	7
1. Behavioural Intention	0.893	0.081	0.036	0.093	0.242	0.160	0.147
2. Control	-0.047	0.873	0.171	0.071	0.320	0.917	0.074
3. Curiosity	-0.032	0.133	1	0.083	0.109	0.121	0.056
4. Immersion	-0.032	-0.037	0.046	0.803	0.143	0.168	0.434
5. Joy	-0.210	0.269	0.109	0.096	1	0.266	0.121
6. Perceived Ease of Use	0.019	0.716	0.105	-0.009	0.225	0.817	0.119
7. Perceived Usefulness	-0.137	0.055	0.027	0.264	0.065	0.074	0.830

Note. Based on authors' calculation; the values below diagonals are showing Fornell and Larcker's Criteria and above are showing HTMT Ratios

the context of this paper, the values of HTMT across all constructs exceeded this threshold (as shown in Table 2). Consequently, these results suggest that there are no issues with discriminant validity in our study.

Structural Model

Prior to estimate the stated hypotheses through the structural model, this paper conducted an examination of multicollinearity assumptions. The assessment revealed that all Variance Inflation Factor

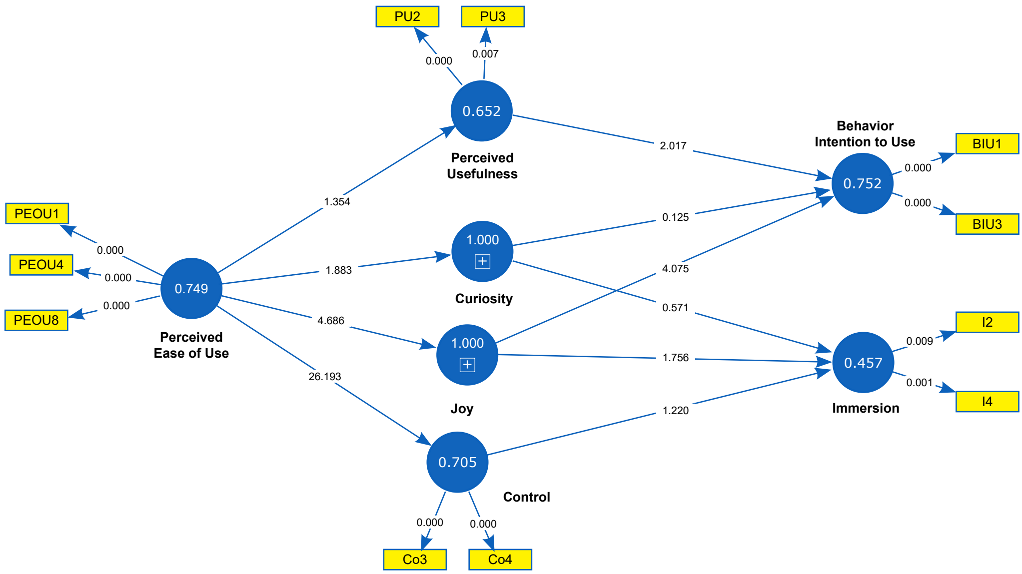


Figure 3. Structural Model

Table 3
Results of Structural Model

Hypotheses	Standardised Beta (β)	T statistics	P values	Decisions
H 1a. PEOU -> CON	0.716	26.193	0.000	Supported
H1b. PEOU -> CU	0.105	1.883	0.060	Unsupported
H1c. PEOU -> JOY	0.225	4.686	0.000	Supported
H1d. PEOU -> PU	0.074	1.354	0.176	Unsupported
H2. PU -> BI	-0.124	2.017	0.044	Supported
H3a. CU -> BI	-0.006	0.125	0.900	Unsupported
H3b. CU -> IMM	0.044	0.571	0.568	Unsupported
H4a. JOY -> BI	-0.202	4.075	0.000	Supported
H4b. JOY -> IMM	0.111	1.756	0.079	Unsupported
H5. CON -> IMM	-0.073	1.22	0.222	Unsupported

Note. Based on authors' calculation; BI: Behavioural Intention; CON: Control; CU: Curiosity; IMM: Immersion; PEOU: Perceived ease of use; PU: Perceived usefulness

(VIF) values remained under 5. Therefore, the structural model estimation proceeded.

The results of Table 3 illustrate that H1a, H1c, H2, and H4a are supported in the study. The results implied that one unit change in PEOU, PEOU, PU, and Joy of ChatGPT increase CON, Joy, BI, and BI by 0.716, 0.225, -0.124, and -0.202 respectively among ChatGPT users.

However, H1b, H1d, H3a, H3b, H4b, and H5 are not supported in the study. The unsupported results implied that the respective relationship among variables is not significant enough to explain ChatGPT Behaviours.

CONCLUSION AND IMPLICATIONS

The paper, focusing on ChatGPT Behaviours among Nepalese Users, utilise HMSAM as the theoretical framework because technology adoption and usage are influenced not only by utilitarian aspects but also by hedonic motivations. By employing HMSAM, the research aims to examine the factors influencing the Adoption Intention of ChatGPT among Nepalese users. The results of the paper are discussed with the existing literature and implications.

First, it is found that PEOU has a significant influence on CON and Joy of the acceptance of ChatGPT usage in the Nepalese context. Previous studies including Deng and Yu (2023); Huda et al. (2020); Lowry et al. (2013); Kari and Kosa (2023), and Oluwajana et al. (2019) consistently showed that PEOU positively influences CON and Joy in various technological contexts. It indicates that ChatGPT users when perceived as easy to use are likely to have control over the communication with ChatGPT and can interrupt the interaction with ChatGPT whenever ChatGPT users want it. This sheds light on understanding the dependency on ChatGPT could be managed with simplicity in its use. When users feel it is easy to use, they perceive autonomy in using ChatGPT rather than becoming over-reliant on this development. However, the paper revealed that PEOU does not influence CU and PU. This unexpected finding underscores the influence of unique factors, including ChatGPT's characteristics on Nepalese users. Users' prior experiences, expectations, and cultural context likely play a more significant role in shaping their perception of usefulness.

Second, it is found that PU has a significant influence on BI among ChatGPT users in the Nepalese context. It is aligned with the findings of previous studies (Deng & Yu, 2023; Huda et al., 2020; Lowry et al., 2013). The perceived usefulness of ChatGPT influences the BI of using ChatGPT. It could provide critical information for the designers and developers of ChatGPT to customise their application to enhance its usefulness among customers. By understanding these technology users' behaviours, they can increase the adoption of ChatGPT.

Third, this paper established that CU does influence BI and IMM. This indicates that in the specific context of ChatGPT interactions in Nepal, factors beyond curiosity, such as perceived usefulness, ease of use, and specific use-case scenarios, may have a more dominant influence on users' decisions. This emphasis es the multifaceted nature of factors influencing immersion in the specific technological context of ChatGPT and suggests that elements beyond joy, such as interaction style and response quality, may exert a more influential role in shaping users' immersive encounters.

Fourth, the paper found that Joy positively influences BI among ChatGPT users. The results align with previous research by Deng and Yu (2023), and Kari and Kosa (2023) which consistently found that enjoyment positively influences users' intentions. This counterintuitive finding suggests that higher levels of Joy may lead to a reduced intention to use ChatGPT, possibly because users' perception could be geared towards recreation rather than practical tasks. It could provide critical information for the designers and developers of ChatGPT to customise their application to enhance the usefulness and joyfulness among customers. By understanding these technology users' behaviours, they can increase the adoption of ChatGPT and improve the overall ChatGPT experience. However, Joy was not a significant variable for IMM of ChatGPT users. The result suggests that elements beyond joy, such as interaction style and response quality, may exert a more influential role in shaping users' immersive encounters.

Finally, this paper found that CON does not play a significant role in IMM among Nepalese ChatGPT users. This suggests that the sense of control may not significantly impact users' immersion within the unique characteristics of ChatGPT interactions in Nepal, potentially due to the nature of these interactions. The scholarly investigation of ChatGPT utilising HMSAM is limited in the Nepalese context. The findings of our study could provide a critical outlook for Nepalese academics and researchers to establish a dialogue with concerned stakeholders to utilise the benefit provided by ChatGPT and mitigate the potential negative consequence of this development.

Limitations and Directions for the Future Research

This paper has several limitations which could provide ground for future researchers. First, this paper investigates ChatGPT adoption by applying the HMSAM model, however, future studies could apply UTAUT to explain ChatGPT usage behaviours. Second, this paper concentrated on individuals aged 20 to 40, predominantly from specific regions within Nepal's provinces. Given that a substantial proportion (75.1%) of respondents belonged to the 20-30 age group. Future studies could be focused on cross-cultural studies. Finally, this paper employed a cross-sectional survey. Future studies could employ a scenario-based survey or experimental design to establish the causality of the model.

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Conflict of interest

The authors declared having no conflict of interest in the research work.

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