

Rethinking Generative AI Continuance in Higher Education: The Mediated Role of Learning Value

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Abstract: In higher education, learning value increasingly drives students' continuous engagement with Generative AI tools such as ChatGPT. By re-conceptualizing the UTAUT framework, this study examines university students' post-adoption and continuance usage intention towards ChatGPT. The study positioned learning value as a mediating variable linking performance expectancy, effort expectancy, perceived trust and hedonic motivation with continuance usage intention. With data collected from 351 university students, this study combines PLS-SEM and ANN analysis to understand both linear and nonlinear relationships among the variables. The findings establish that learning value is the strongest driver of continuance usage intention and significantly mediates the effect of performance expectancy, effort expectancy and hedonic motivation while perceived trust has a significant direct influence on continuance intention, with no mediating effect with learning value. Effort expectancy, on the other hand, does not have a significant influence on continuance intention, suggesting that ease of use has become a hygiene factor in the post-adoption learning context. The results highlight the importance of re-conceptualizing the UTAUT model towards a learning-centered approach where educational value, an interactive user interface and trustworthiness drive continuous usage intention of Generative AI tools. The findings highlight the importance of integrating Gen-AI tools into pedagogical designs that promote critical thinking rather than using them for mere task completion. This paper suggests longitudinal and cross-country comparisons examining the ethical and responsible use of ChatGPT in the learning process of university students as the scope for future research.

Keywords: Learning Value; Gen-AI in Higher Education; ChatGPT Continuance Usage Intention; SEM-ANN Hybrid Analysis

1. Introduction

The learning landscape has witnessed a momentous change in the recent past with the increasing use of Generative Artificial Intelligence (Gen-AI) tools. Both students and teachers are adopting Gen-AI tools such as ChatGPT which profoundly impacts how students learn and teachers teach [1]. This technological advancement has evolved to become the ultimate learning tool for students due to its ability to create human-like conversational responses in a manner that supports various learning capacities [2].

Students in higher education such as universities are embracing ChatGPT to help them learn better. Apart from basic use of completing assignments [3], students see ChatGPT as a learning companion that helps them with homework, supports them with assignments and essay writing [4], explains difficult concepts in an easy-to-understand manner [5], and even generates resources to test

their conceptual understanding [2]. By offering personalized learning experiences, ChatGPT is strengthening students' learning process and raising engagement, potentially creating a transformative force in higher education whose implications are still being explored [6].

While the use of ChatGPT among university students is growing rapidly, there is still a dearth of understanding in the factors that encourage students to continue using Gen-AI tools in their learning process. This study therefore focuses on exploring students' continuous usage intentions (CI) of ChatGPT by identifying the key factors that drive the intention. According to [7], continuance usage intention may be defined as an individual's likelihood to continue using a specific system, in this case, students' continuance usage intention of ChatGPT for learning purposes.

The increasing popularity of ChatGPT as a learning tool has sparked the curiosity of many researchers to understand the exact factors that trigger the behavioral and continuance usage intentions among students to use ChatGPT. A number of theoretical frameworks have been used to understand this behavior, popular among which are Technology Acceptance Model (TAM) [8] [9], Diffusion of Innovation Theory [10], Stimulus-Organism-Response [11], the Unified Theory of Acceptance and Use of Technology (UTAUT) [12, 13, 14], and UTAUT2 [15, 16, 17], among others. This research is based on the most common UTAUT model [18] to understand if traditional technology adoption theory holds in the Gen-AI learning context.

Despite the growing interest, research gaps still remain. Firstly, despite the popularity of the UTAUT model in understanding technological adoption in various fields, it does not include factors such as trust in Gen-AI generated results and the direct educational value derived from such tools by university students [17, 19, 20]. This paper aims to address this gap by extending the UTAUT model by incorporating factors such as perceived trust, learning value and hedonic motivation. Conversely, factors such as social influence and facilitating conditions, found to be less relevant in prior studies, are excluded [13, 15, 17, 19].

Secondly, existing studies provide inconsistent findings regarding the exact impact of performance expectancy and effort expectancy as drivers of ChatGPT adoption, with some studies indicating weak or non-significant effects [11, 12, 16, 17]. The discrepancies in the findings of current work in the field of Gen-AI are another motivation for this study, as it seeks to re-examine these variables and their influence on the usage of ChatGPT by students.

Thirdly, although prior studies have extensively used the UTAUT framework, a significant theoretical gap remains regarding the limited attention given to learning value as a central mechanism that drives continuous usage behavior for educational purposes. In an academic setting, students not only use ChatGPT as a productivity tool in terms of completing assignments but also as a learning system that supports overall academic development through feedback, explanation and engagement. Yet, learning value has received limited attention as a mediating variable in Gen-AI research. Positioning learning value as a mediating mechanism offers a more education-centered explanation of ChatGPT usage among university students.

Fourthly, most studies have been conducted in high- and middle-income countries. Much less is known about continuous usage in developing countries such as Bangladesh, where cultural, linguistic, and pedagogical contexts differ significantly [21]. Exploring Bangladeshi students' perspectives therefore provides valuable insights into Gen-AI usage within distinct educational and cultural settings.

Finally, this paper differentiates itself from existing research by taking on a unique methodological approach by combining Partial Least Squares Structural Equation Modelling (PLS-SEM) along with Artificial Neural Network (ANN) with the aim of strengthening the analytical accuracy. While most existing work focuses on PLS-SEM, this study tests deductive relationships through PLS SEM while understanding the more complex non-linear patterns and interaction effects through ANN. Additionally, the use of the ANN approach allows for the ranking of the predictors using linear and non-linear factors, which further strengthens the contributions of this paper.

As the educational system around the world evolves and incorporates AI tools in the learning process at all levels, it becomes important to understand the intentions of students towards such learning tools. This paper becomes very timely and relevant as it aims to guide the higher-education policymakers on the extent to which AI must be integrated into the system while also signaling which factors require greater attention. Incorporating additional theoretically backed variables with a multi-method analytical design, this paper aims to contribute to broader theory on how students in higher education evaluate and use Gen-AI tools such as ChatGPT.

2. Literature Review and Hypothesis Development

Past research exploring areas of technological adoption across multiple industries and geographical locations has used the Unified Theory of Acceptance and Use of Technology (UTAUT) as the preferred theoretical framework due to the model's relative robustness and its strong explanatory power. Developed by [18], this framework explores and integrates eight previously established theories and identifies four key determinants of behavioral intentions: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI) and Facilitating Conditions (FC). As per the model, PE represents the extent to which users believe technology will improve task performance; EE stands for perceived ease with which the given technology can be used; SI takes into account the importance of peers and others in the decision to adopt the technology while FC is the ease with which necessary resources and technical support can be availed to use the technology.

This paper has built upon the theoretical foundation of UTAUT and modified the model by introducing learning-centric and experiential dimensions of technology use. The need for such a model modification arises from the uniqueness of ChatGPT as compared to other forms of technology, which, if ignored, will limit the ability of this study to holistically analyze the educational benefits derived from ChatGPT. The main modification lies in the exclusion of Facilitating Conditions (FC) and Social Influence (SI), which were removed on theoretical grounds.

In the original model, FC refers to the perceived availability of the technical resources, organizational support, and infrastructure required to use a technology. FC is expected to be more pronounced when users depend on technical support or formal training [18]. ChatGPT, however, is a readily accessible, browser and app-based tool that requires only basic internet connectivity and modest computing resources [17, 19]. As university students generally have access to these basic resources, and ChatGPT can be used through an intuitive natural language interface, technical support is unlikely to represent a significant barrier to continued use. Consequently, the enabling conditions captured by FC are likely to vary little among the students in this study, limiting their ability to explain differences in continuance intention.

A similar argument applies to SI. UTAUT suggests that SI is particularly important during the early stages of technology adoption and in situations where users have limited direct experience with

the technology [18]. Its influence is expected to decline as users gain personal experience and become more confident in evaluating the technology independently. This study focuses specifically on the post-adoption stage, examining students' continuance intention toward a voluntarily used and individually accessed tool. This context therefore falls within the conditions under which UTAUT itself suggests that SI should become less influential. This argument is also consistent with the broader continuance literature [7], which emphasizes users' own post-adoption experiences and evaluations rather than normative social pressures as drivers of continuance usage intention.

Furthermore, in educational contexts, students typically use ChatGPT as a personalized academic assistant for activities such as problem solving, obtaining feedback, and clarifying difficult concepts. Consequently, peer expectations or social pressure are likely to play a limited role in post-adoption decisions, particularly once students have gained sufficient personal experience with the technology [15, 17]. Empirical evidence from comparable ChatGPT adoption studies further supports the limited relevance of SI and FC in this context [13, 15]. Accordingly, SI and FC are omitted because the conditions under which they are expected to be most influential do not closely characterize post-adoption use of a freely accessible conversational AI tool such as ChatGPT.

On the other hand, this study includes two additional independent variables: Perceived Trust (PT) and Hedonic Motivation (HM), and Learning Value (LV) is added as a mediator. PT is included to assess the issues of accuracy, reliability and bias that may arise as ChatGPT draws information from multiple sources before generating its own response; HM reflects the experiential dimension of use satisfaction and the enjoyment users derive from interacting with AI through a human-like conversational interface such as ChatGPT. LV addresses the academic benefits that students believe they derive from using AI and therefore plan to continue its usage for academic purposes.

The UTAUT model has been applied extensively and continues to serve as a robust and widely accepted theoretical framework [22]. Recent research highlights its reliability in explaining students' acceptance of emerging technologies, including generative AI applications such as ChatGPT, across different cultural and educational settings [17, 22]. By adapting the framework, this study not only extends the UTAUT model to the context of generative AI but also offers practical insights for educators and policymakers aiming to integrate ChatGPT into higher education in a responsible and effective manner.

2.1. Hypothesis Development

2.1.1. Performance Expectancy (PE)

One of the most important factors influencing technology adoption is performance expectancy (PE). PE refers to the extent to which a user finds a tool to be useful and believes that it will improve task performance [18]. In the case of ChatGPT, this could refer to the extent to which students believe that ChatGPT will help them to improve their academic performance. Both [19] and [17] found that PE is directly linked to ChatGPT usage among university students. Similarly, [23] and [14] also reported that PE strongly shapes students' intentions to use ChatGPT in higher education contexts.

However, apart from the direct influence of PE on continuance usage intention, PE can also significantly improve learning efficiency which will influence students' intention to continue using ChatGPT for academic purposes. For example, the ability of ChatGPT to assist in most tasks not only saves students' time but also supports them in writing and comprehension skills that help them to complete academic tasks more quickly and easily [24, 25]. Such assistance enhances the overall

learning experience. This perceived learning value will further strengthen their continuance usage intention towards ChatGPT. Therefore, it is proposed that PE will influence continuance usage intention both directly and through the mediating factor of learning value.

Accordingly, the following hypotheses are proposed:

H1a: Performance expectancy positively influences learning value

H1b: Performance expectancy positively influences students' continuance intention to use ChatGPT.

H1c: Learning value mediates the relationship between performance expectancy and continuance intention

2.1.2. Effort Expectancy (EE)

EE looks into the extent a tool is perceived to be simple and easy to use [18]. In the case of ChatGPT, EE refers to the degree to which students believe the system is easy to learn, interact with, and apply for academic purposes. When technology is considered to be difficult to use and requires additional effort to engage with, the perceived costs are likely to outweigh the benefits [26]. Previous research by [19] and [17], however, emphasizes that the usage of ChatGPT is very similar to using online information search and therefore the simplicity would encourage persistent and frequent use.

Furthermore, the ease of interaction can also help students to focus more on learning outcomes. As ChatGPT uses a simple and conversational interface, students will seldom face operational difficulties and will require less effort to master it. This helps students to focus and engage more deeply with a topic, increasing the educational benefits and learning value from the system. Therefore, based on the notion that simplicity and ease of use will help students to learn better which in turn will strengthen their continuance usage intention, the following hypotheses are proposed:

H2a: Effort expectancy positively influences learning value

H2b: Effort expectancy positively influences students' continuance usage intention

H2c: Learning value mediates the relationship between effort expectancy and continuance intention

2.1.3. Perceived Trust (PT)

In this study, the perception of students regarding the reliability and trustworthiness towards technology is referred to as Perceived Trust (PT) [27]. PT has been established as a crucial determinant in the adoption of technology in both digital and educational spheres [28, 29]. Given the accuracy issues that may arise from Gen-AI tools, the concept of PT plays an integral role in determining a user's intention to continue interacting with such technology [30, 31].

Trust was found to moderate the relationship between perceived enjoyment and attitudes towards ChatGPT among Bangladeshi students, which consequently influenced their usage intentions towards the tool [32]. Therefore, it can be assumed that students are more likely to use ChatGPT regularly when they believe it is reliable, secures their privacy and improves the quality of their work. On the contrary, the overuse of such technology in the form of a "blind trust" may adversely affect the quality of judgement; while low trust can lead to underutilization of ChatGPT and lapsed learning opportunities [33].

Despite the pivotal role played by PT as a determining factor in the continuous usage of ChatGPT for academic purposes, the importance of PT in influencing learning value remains relatively underexplored. For instance, in an academic setting, reliability and correctness of outputs

are of utmost importance to support students in their academic work. Only when students can trust and rely on the outputs generated by ChatGPT, they are more likely to perceive it as academically beneficial which will translate into sustained usage behavior. Thus, students' perceptions of ChatGPT's reliability and trustworthiness in supporting academic work will influence the learning value of the tool. Addressing this gap, it is believed that higher levels of PT will positively influence learning value and students' continuance usage intention of ChatGPT for assessment-related purposes. As such the following hypotheses are proposed:

H3a: Perceived trust positively influences learning value

H3b: Perceived trust positively influences students' continuance usage intention

H3c: Learning value mediates the relationship between perceived trust and continuance intention

2.1.4. Hedonic Motivation (HM)

Hedonic motivation (HM) refers to 'the degree to which an individual is driven to use a particular technology for its inherent enjoyment, pleasure, or novelty [34]. Research has demonstrated that HM is a critical factor in educational technology adoption especially among university students [35].

Similarly, it is to be believed that if students enjoy the interaction with ChatGPT and find it entertaining, they are more likely to use it in everyday learning. This is more likely to be true as the conversational and human-like response of ChatGPT creates an engaging learning experience that drives students' adoption of ChatGPT [15]. ChatGPT's interactive and engaging features have been reported to make learning enjoyable for students [36].

Apart from directly influencing continuance usage intention, HM may also make the learning process more enjoyable and engaging, leading students to spend more time exploring different topics and experimenting with different prompts. This deep engagement directly influences learning value thereby converting a pleasurable experience into an academically valuable one. This intrinsic enjoyment can significantly influence students' continuance usage intentions. Based on the fun, pleasurable, and engaging interface of ChatGPT, the following hypotheses are proposed:

H4a: Hedonic motivation positively influences learning value

H4b: Hedonic motivation positively influences students' continuance usage intention

H4c: Learning value mediates the relationship between hedonic motivation and continuance intention

2.1.5. Learning Value (LV)

Learning value (LV) in educational technology research refers to students' perceptions of how a tool supports their learning by saving time, enhancing knowledge acquisition, and improving the overall learning process [37]. Prior research consistently identifies LV as a key determinant of students' intention to adopt and use educational technologies [38, 39]. Students are generally more willing to use platforms they perceive as genuinely useful for improving their learning outcomes [35, 40].

In the case of ChatGPT, the ability to provide detailed explanations, offer instant feedback on uploaded work, and correct and polish writing style all improve students' learning ability which ultimately improves academic performance. Previous studies support this view as ChatGPT is found to be useful in clarifying difficult topics and improving academic performance. This motivates

students to use ChatGPT in the learning process [24]. This study therefore conceptualizes LV as a central determinant of students' continuance intention to use ChatGPT for academic support. Based on this, the following hypothesis is proposed:

H5: Learning Value will positively influence students' continuance usage intention

2.1.6. Continuance Usage Intention (CI)

Continuance usage intention (CI) refers to an individual's subjective likelihood to continue using a particular technology in the future [7]. In the context of this study, CI captures the extent to which students intend to continually use ChatGPT in their academic activities, for learning and assessment-related support. The work of [41] established that CI reflects an individual's intention to continue using a specific service is an essential aspect for information systems. Studying CI will enable this paper to understand the patterns followed in sustained technological usage process of students. The findings of this paper aim to maximize the benefits that students can derive from ChatGPT by aiding in the formation of strategies that further integrate its use in the education system. Figure 1 presents the conceptual model of this study.

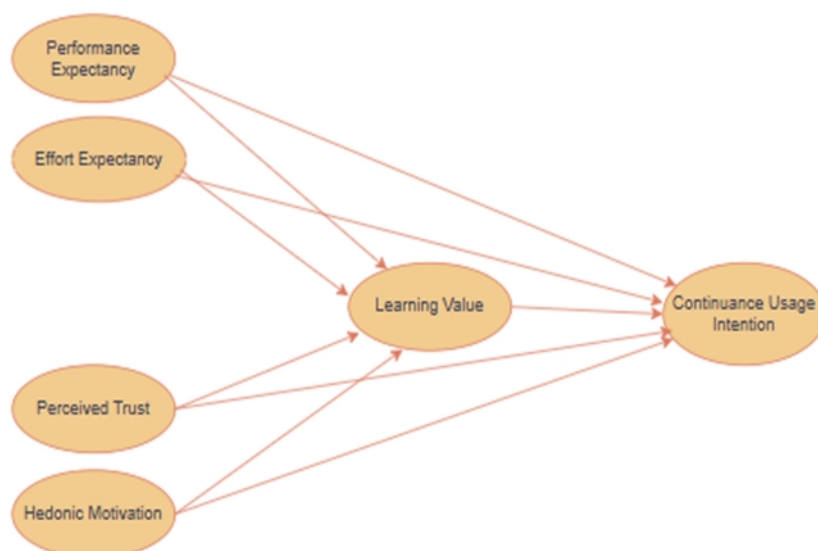


Figure 1. Conceptual Framework

3. Materials and Methods

3.1. Research Design

This study combines Partial Least Squares Structural Equation Modelling (PLS- SEM) with Artificial Neural Networks (ANN) to form a hybrid analytical approach. The research design follows a quantitative cross-sectional survey to determine university students' continuance usage intention of ChatGPT for academic purposes. While PLS-SEM enables testing of the linear hypothesized relationships between the variables and assesses the explanatory power of the proposed model; ANN aims to capture and understand the non-linear patterns and accordingly evaluate varying importance of the independent variables.

3.2. Questionnaire Design

A structured questionnaire comprising 25 measurement items was used to assess the variables. Previously validated scales were used to maintain the reliability and validity of the constructs where

items for Performance Expectancy (4 items), Effort Expectancy (4 items) and Continuance Usage Intention (3 items) were adapted from [17], Perceived Trust (6 items) was derived from the work of [33], Hedonic Motivation (4 items) was based on the work of [42], and Learning Value (4 items) was adapted from the study by [15]. Responses were recorded on a five-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

3.3. Sampling and Data Collection

This study collected responses from current university students in Bangladesh who had prior experience using ChatGPT for academic purposes since continuance usage intention is only meaningfully reported by individuals with direct post-adoption experiences. To ensure this, screening questions were included at the beginning of the questionnaire to filter out non-users. The study adopted a non-probability purposive sampling method as no complete sampling frame of existing students who use ChatGPT for academic purposes was available [43]. Data were collected using online questionnaires distributed through Google Forms. The data were screened for missing values and unengaged respondents (identified through straight-lining responses), giving a final sample of 351 valid responses, comprising 300 undergraduates (85.5%) and 51 graduate students (14.5%). The sample represented several academic disciplines, including science and engineering (45.6%), business and economics (34.4%), arts and humanities (8.6%), social sciences (5.7%) and other fields (6%). This interdisciplinary diversity allowed the study to capture post-adoption usage of ChatGPT across different academic disciplines. The minimum required sample size was determined as per [44] 5:1 or 10:1 ratio. Given that this study involved 25 measurement items, a minimum sample size of 250 was deemed appropriate. The final sample of 351 respondents therefore exceeded the minimum requirement. An overview of the respondents' demographic characteristics is presented in Table 1.

Table 1. Demographic Profile

Category	Subcategory	Count	Percentage(%)
Gender	Male	224	63.8
	Female	127	36.2
Age Group	19-22	105	29.9
	23-30	235	67
	31 and above	11	3.1
Academic Level	Undergraduate	300	85.5
	Graduate	51	14.5
Field of Study	Science & Engineering	160	45.6
	Business & Economics	120	34.4
	Arts & Humanities	30	8.6
	Social Science	20	5.7
	Other	21	6

3.4. Data Analysis Procedure

3.4.1. PLS-SEM Analysis

This paper follows a two-step approach to the analysis, wherein the measurement model is first evaluated, followed by the assessment of the structural model. SmartPLS Version 4.1.1.6 was used as

the analytical tool to study the multivariate relationships among the constructs due to its robustness and flexibility in analyzing both direct and indirect effects. The modification of the UTAUT model through the inclusion of new predictors has made this research partially exploratory. Therefore, PLS-SEM is the more suitable approach for analysis rather than Covariance-Based Structural Equation Modelling (CB-SEM) as the latter is better suited for theory confirmation rather than theory extensions [45]. Bootstrapping with 5,000 subsamples was used to determine the significance of path coefficients.

3.4.2. Artificial Neural Networks (ANN) Analysis

Artificial Neural Networks (ANN) are supervised learning models that, unlike regression-based approaches, can capture potential non-linear relationships between predictors and outcomes through iterative learning rather than pre-specified relationships [46]. ANN analysis was chosen to complement the PLS-SEM linear relationship results as it can capture potential non-linear relationships and assess the relative predictive importance of the constructs. SPSS 25 was used to perform the ANN analysis. A feed-forward back-propagation multilayer perceptron (MLP) architecture was chosen, as MLPs have consistently demonstrated superior predictive accuracy compared to traditional regression approaches [47].

The usual composition of an ANN model is as follows: an input layer, one or more hidden layers and an output layer. For this study a single hidden layer was deemed sufficient given its theoretical capacity to estimate any continuous function [48]. Therefore, to ensure the model is robust, the dataset was accordingly divided into training (80%) and testing (20%) subsets for validation purposes. Following [49]'s recommendation, the hyperbolic tangent activation function was used to enhance learning efficiency and overall performance. In both models, the number of hidden neurons was determined through SPSS's automatic selection procedure rather than fixed in advance. This procedure trains and compares networks across different ranges and retains the architecture with the best predictive performance. The resulting architecture is not necessarily identical across the two models since each model's optimal complexity is determined independently from its own data [48]. Furthermore, to generate the ten ANN models, a randomized MLP repetitive training procedure was chosen where each repetition generated a fresh random 80/20 split and no fixed random seed was specified.

While PLS-SEM evaluates direct, indirect and the mediating effects simultaneously within a single integrated structural path, the standard feed-forward Back-Propagation MLP architecture cannot model dual endogenous and mediating constructs within a single feedforward pass. To overcome this architectural constraint, two sequential ANN models were specified to mirror the two-stage mediating structure of the PLS-SEM model. ANN model 1 (figure 2) predicts learning value (LV, mediating variable) from PE, EE, PT and HM with automatic architecture selection yielding six hidden neurons in the network shown. ANN model 2 (figure 3) predicts continuance usage intention (CI, ultimate endogenous variable) from PE, EE, PT, HM and LV with the automatic architecture selection procedure yielding four hidden neurons in the network shown.

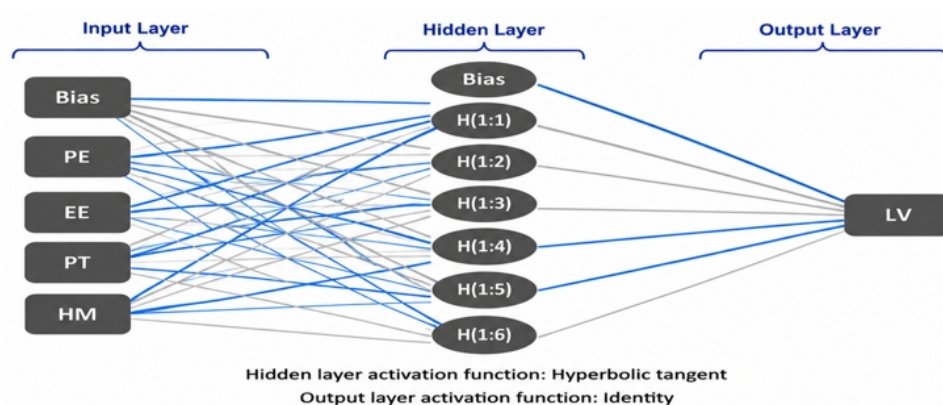


Figure 2. ANN Model 1 (6 Hidden Neurons): Input (PE, EE, PT, HM); Predicting Output (LV)

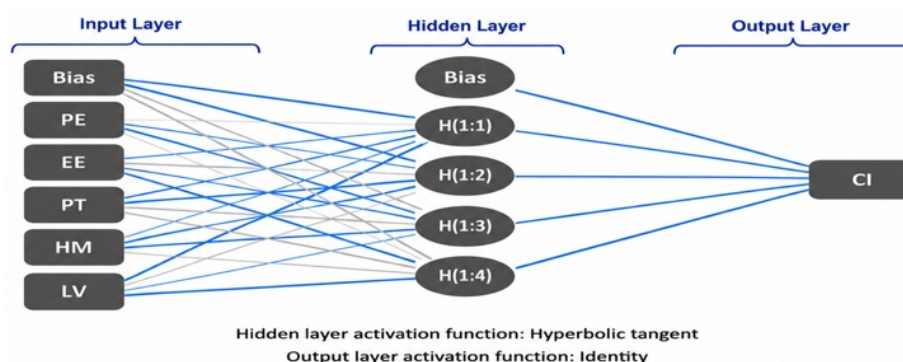


Figure 3. ANN Model 2 (4 Hidden Neurons): Input (PE, EE, PT, HM, LV); Predicting Output (CI)

The two ANN models and the PLS-SEM mediation test therefore represent the same mediating pathway through different estimation methods. PLS-SEM captures it within one simultaneous, linear model, while ANN requires two sequential, non-linear models to approximate the equivalent path. This follows the established practice in the hybrid SEM-ANN literature for handling mediators that cannot be jointly estimated within a single feed-forward architecture [47, 48, 50].

Model performance was assessed using root mean square error (RMSE), which measures the difference between predicted and observed values where lower RMSE values indicate better predictive accuracy [50]. Following model estimation, sensitivity analysis was conducted to determine the relative importance of each predictor, normalized as a percentage of the highest importance predictor which was assigned a value of 100% to allow comparison across variables [51].

4. Results

4.1. Common Method Bias

Since the data were collected from a single source, the potential issues of common method bias (CMB) may be present. Self-reported survey designs are likely to have common method variance (CMV) which may create false relationships between the constructs [52]. Harman's Single-Factor Test [52] was first conducted. The results showed that the first factor explained 40.649% of the variance, which is below the recommended threshold of 50%, suggesting that CMB is not a major concern in this study [53]. Additionally, a full collinearity assessment was conducted [54]. The variance inflation factor (VIF) values for all constructs were below 3.33, further confirming that CMB is not a serious issue in this study.

4.2. Measurement Model Assessments

This study has six latent variables with reflective measurement models. To measure reflective measurement models, outer loadings were estimated first to check for indicator reliability. A loading value of 0.70 is generally regarded as the threshold for acceptable indicator reliability [45]. As shown in Table 2, 22 items exceeded this threshold. However, items PT1 (0.683), PT2 (0.688), and PT6 (0.689) were excluded from further analysis because their loadings fell below the recommended benchmark. Accordingly, the final model was estimated using 22 items. All reported measurement and structural model results are based on the final estimated model with 22 items.

Table 2. Measurement Model Analysis

Construct	Items	Loading	CA	CR	AVE
Performance Expectancy - PE	PE1	0.828	0.822	0.827	0.652
	PE2	0.807			
	PE3	0.814			
	PE4	0.779			
Effort Expectancy - EE	EE1	0.801	0.813	0.817	0.64
	EE2	0.767			
	EE3	0.794			
	EE4	0.836			
Perceived Trust - PT	PT1	0.683	0.7	0.704	0.624
	PT2	0.688			
	PT3	0.749			
	PT4	0.703			
	PT5	0.7			
Hedonic Motivation - HM	PT6	0.689	0.803	0.804	0.629
	HM1	0.789			
	HM2	0.796			
	HM3	0.794			
Learning Value-LV	HM4	0.791	0.8	0.801	0.624
	LV1	0.788			
	LV2	0.797			
	LV3	0.793			
Continuous Usage Intention - CI	LV4	0.783	0.797	0.801	0.711
	CI1	0.822			
	CI2	0.861			
	CI3	0.846			

Next, construct reliability was measured using Cronbach alpha and composite reliability with values above 0.70 considered to be acceptable [45]. Convergent validity was tested using the average variance extracted (AVE) method, which measures how much of the variance in the indicators is explained by their underlying construct. A minimum AVE value of 0.50 or above suggests adequate construct validity [55]. As shown in Table 2, all constructs exceeded the recommended thresholds for Cronbach's alpha, composite reliability, and AVE, confirming the reliability and validity of the measurement model.

Next, discriminant validity (Table 3) was assessed using the Fornell–Larcker criterion [56]. This method requires that the square root of each construct's AVE should be greater than its correlations with other constructs. The analysis confirmed that all constructs satisfied this condition thereby

meeting the recommended standards for discriminant validity [45]. Moreover, HTMT values for all constructs are below the recommended threshold of 0.85, further confirming discriminant validity [45] (Table 4). Although the HTMT ratio between hedonic motivation and learning value was 0.847, close to but below the conservative threshold, this borderline value nevertheless remains further below the more liberal 0.90 threshold, providing support for empirical distinctiveness of the two constructs [45].

Table 3. Assessment of Discriminant Validity - Fornell-Larcker Criterion

	CI	EE	HM	LV	PE	PT
CI	0.843					
EE	0.575	0.8				
HM	0.62	0.669	0.793			
LV	0.662	0.627	0.681	0.79		
PE	0.604	0.668	0.628	0.636	0.807	
PT	0.512	0.544	0.488	0.45	0.558	0.79

Table 4. Assessment of Discriminant Validity – HTMT Ratio

	CI	EE	HM	LV	PE	PT
CI						
EE	0.707					
HM	0.768	0.823				
LV	0.827	0.772	0.847			
PE	0.742	0.81	0.767	0.78		
PT	0.682	0.715	0.644	0.596	0.724	

4.3. Structural Model Assessments

Following the structural model assessment procedure outlined by [45], collinearity was first assessed by examining the Variance Inflation Factor (VIF) values of all the predictors. In this study, all VIF values were below the recommended threshold of 3.0, indicating that multi-collinearity was not a critical issue in the structural model [45] (see Table 5).

Table 5. Test of Hypothesis

Path Relationship	Beta Value	SD	T-Value	P values	f-square	VIF	Hypothesis
H1a: PE -> LV	0.263	0.07	3.857	0	0.071	2.18	Accepted
H2a: EE -> LV	0.186	0.05	3.422	0.001	0.033	2.32	Accepted
H3a: PT -> LV	0.017	0.06	0.299	0.765	0	1.59	Rejected
H4a: HM -> LV	0.383	0.05	7.138	0	0.16	2.05	Accepted
H1b: PE -> CI	0.151	0.06	2.507	0.012	0.021	2.33	Accepted
H2b: EE -> CI	0.055	0.06	0.881	0.378	0.003	2.4	Rejected
H3b: PT -> CI	0.158	0.06	2.86	0.004	0.034	1.59	Accepted
H4b: HM -> CI	0.182	0.07	2.656	0.008	0.03	2.38	Accepted
H5: LV -> CI	0.337	0.06	5.622	0	0.11	2.23	Accepted

Next, the significance of the structural model was assessed by bootstrapping with 5,000 subsamples. As shown in table 5, the strength of each relationship can be identified by beta path coefficients while the significance of both direct and indirect relationships was evaluated using t-statistics and p-values, with t-values above 1.96 and p-values below 0.05 considered statistically significant. The direct relationships tested the effects of the independent variables (PE, EE, PT, HM)

on both the mediator (LV) and the final dependent variable, continuance usage intention (CI). For the mediation analysis of LV, specific indirect effects were analyzed (Table 6).

Table 6. Mediation Analysis

Path	Direct Effect	P-Value (Direct)	Indirect Effect	P-Value (Indirect)	Conclusion
H1c: PE -> LV -> CI	0.151	0.012	0.088	0.001	Partial Mediation
H2c: EE -> LV -> CI	0.055	0.378	0.063	0.004	Full Mediation
H3c: PT -> LV -> CI	0.158	0.004	0.006	0.764	No Mediation
H4c: HM -> LV -> CI	0.182	0.008	0.129	0	Partial Mediation

The results in table 5 indicate that performance expectancy has a positive and significant influence on both learning value ($\beta = 0.263$, $t = 3.857$, $p < 0.001$) and continuance usage intention ($\beta = 0.151$, $t = 2.507$, $p = 0.012$) supporting both H1a and H1b. The mediation analysis further showed that the specific indirect effect of PE on CI through learning value is also significant ($\beta = 0.088$, $p = 0.001$). As both the direct and indirect effects are significant, learning value partially mediates the relationship between PE and CI, confirming H1c and indicating complementary partial mediation (Table 6).

Next, it can be seen from table 5 that effort expectancy positively influences learning value ($\beta = 0.186$, $t = 3.422$, $p < 0.001$) supporting H2a. Interestingly, the direct relationship between EE and CI is statistically not significant ($\beta = 0.055$, $t = 0.881$, $p = 0.378$) thereby rejecting H2b. However, the specific indirect effect of EE on CI through learning value is significant ($\beta = 0.063$, $p = 0.004$) suggesting full mediation, supporting H2c (Table 6).

Perceived trust does not have a significant influence on learning value ($\beta = 0.017$, $t = 0.299$, $p = 0.765$), hence H3a is not supported. Conversely, PT significantly influences CI ($\beta = 0.158$, $t = 2.860$, $p = 0.004$) supporting H3b. The specific indirect effect of PT on CI through learning value was also insignificant ($\beta = 0.006$, $p = 0.764$) leading to rejection of H3c, indicating no mediation and suggesting that PT directly influences CI (Table 6).

Next, hedonic motivation was found to have significant effect on both learning value ($\beta = 0.383$, $t = 7.138$, $p < 0.001$) and continuance usage intention ($\beta = 0.182$, $t = 2.656$, $p = 0.008$) supporting both H4a and H4b. Furthermore, the mediation analysis confirms that the specific indirect effect of HM on CI through learning value is also significant ($\beta = 0.129$, $p < 0.001$), confirming complementary partial mediation and supporting H4c (Table 6). Finally, the impact of learning value on continuance usage intention was found to be significant ($\beta = 0.337$, $t = 5.622$, $p < 0.001$), confirming the acceptance of H5 (Table 5).

Lastly, the R^2 value was examined to assess the model's explanatory power with values ranging from 0 to 1 where higher values indicate stronger explanatory power (Table 7). According to [57], an R^2 value of 0.552 for LV and 0.539 for CI would reflect moderate explanatory power. The results indicate that approximately 55.2% of the variance in LV is explained by PE, EE, PT, HM while the model explains 53.9% variance on CI. These results suggest that the proposed model demonstrates satisfactory explanatory power in predicting both learning value and continuance usage intention towards ChatGPT. In addition, the model's out-of-sample predictive relevance was evaluated through Q^2 value using blindfolding procedures (Table 7). The Q^2 values for both learning value ($Q^2 = 0.539$) and continuance usage intention ($Q^2 = 0.473$) are substantially above zero, indicating that the model has strong predictive relevance for these specific endogenous constructs.

Table 7. Explanatory Power and Predictive Relevance

	R-square	R-square adjusted	Q ² predict
LV	0.552	0.547	0.539
CI	0.539	0.532	0.473

4.4. ANN Analysis

The ANN analysis complements the PLS-SEM findings by examining predictive performance and the relative importance of the predictors under potentially non-linear conditions. The predictive performance of the networks was assessed using RMSE. For ANN model 1, the mean RMSE was 0.487 for the training data and 0.467 for the testing data, with a mean difference of 0.020. For ANN model 2, the corresponding mean RMSE values were 0.492 for training and 0.480 for testing, with a mean difference of 0.012. The relatively small differences between training and testing RMSE values across the ten networks indicate strong predictive performance and provide no indication of substantial overfitting between the training and testing subsets. The individual network results are reported in table 8.

Table 8. Neural Network RMSE Values

Network	RMSE (Training)	RMSE (Testing)	RMSE (Difference)	Network	RMSE (Training)	RMSE (Testing)	RMSE (Difference)
ANN 1	0.485	0.437	0.048	ANN 1	0.500	0.453	0.048
ANN 2	0.462	0.490	0.028	ANN 2	0.514	0.442	0.072
ANN 3	0.487	0.514	0.027	ANN 3	0.484	0.526	0.041
ANN 4	0.506	0.443	0.063	ANN 4	0.474	0.432	0.042
ANN 5	0.493	0.518	0.025	ANN 5	0.480	0.578	0.098
ANN 6	0.514	0.537	0.023	ANN 6	0.538	0.465	0.072
ANN 7	0.477	0.461	0.016	ANN 7	0.468	0.422	0.045
ANN 8	0.462	0.402	0.060	ANN 8	0.478	0.493	0.015
ANN 9	0.483	0.413	0.070	ANN 9	0.515	0.549	0.033
ANN 10	0.504	0.460	0.044	ANN 10	0.472	0.438	0.035
Mean	0.487	0.467	0.020	Mean	0.492	0.480	0.012
St Dev	0.018	0.046	0.028	St Dev	0.023	0.054	0.031
ANN Model 1: IV [PE, EE, PT, HM] , DV [LV]				ANN Model 2: IV [PE, EE, PT, HM, LV] , DV [CI]			

Table 9 presents the sensitivity analysis results. In ANN Model 1, hedonic motivation was the strongest predictor of learning value (normalized importance = 100%), followed by effort expectancy (68.76%), performance expectancy (46.18%), and perceived trust (17.12%). In ANN Model 2, learning value was identified as the strongest predictor of continuance usage intention (100%) followed by perceived trust (41.04%), hedonic motivation (36.20%), performance expectancy (33.41%) and effort expectancy (12.89%).

Table 9. Sensitivity Analysis

ANN Model 1	PE	EE	PT	HM	ANN Model 2	PE	EE	PT	HM	LV
NN1	0.186	0.292	0.062	0.460	NN1	0.151	0.068	0.179	0.283	0.319
NN2	0.170	0.324	0.041	0.465	NN2	0.096	0.008	0.189	0.074	0.632
NN3	0.026	0.338	0.110	0.526	NN3	0.206	0.039	0.208	0.097	0.450
NN4	0.270	0.227	0.041	0.461	NN4	0.100	0.022	0.192	0.174	0.512
NN5	0.287	0.159	0.037	0.517	NN5	0.145	0.080	0.225	0.190	0.360
NN6	0.235	0.277	0.096	0.392	NN6	0.108	0.138	0.176	0.196	0.382
NN7	0.153	0.383	0.102	0.362	NN7	0.169	0.023	0.149	0.132	0.527
NN8	0.135	0.531	0.088	0.246	NN8	0.152	0.048	0.137	0.215	0.448

ANN Model 1	PE	EE	PT	HM	ANN Model 2	PE	EE	PT	HM	LV
NN9	0.210	0.192	0.073	0.526	NN9	0.216	0.115	0.161	0.150	0.357
NN10	0.318	0.241	0.087	0.354	NN10	0.152	0.035	0.218	0.107	0.487
Average Importance	0.199	0.296	0.074	0.431	Average Importance	0.149	0.058	0.184	0.162	0.447
Normalized Importance	46.18%	68.76%	17.12%	100%	Normalized Importance	33.41%	12.89%	41.04%	36.20%	100%

5. Discussion

The purpose of this study was to understand students' intention to continue using ChatGPT in their studies by adopting a hybrid analytical approach. The study extended the UTAUT framework by adding constructs such as perceived trust and hedonic motivation while positioning learning value as a mediator. As most of the initial studies focused heavily on ChatGPT adoption, this study addresses the critical yet understudied gap of students' long-term intention to use ChatGPT for learning purposes.

Performance expectancy was found to positively and significantly influence both learning value and continuance intention which is consistent with earlier studies [15, 17, 19]. Based on the results, it can be understood that ChatGPT's advanced generative AI features allow students to clarify their doubts and provide the needed feedback; resulting in greater student reliance on the tool for their academic progress. This perceived usefulness, in turn, encourages students to continue using ChatGPT for learning-related activities.

However, while PE ranked relatively high in predicting learning value across both PLS-SEM (rank 2) and ANN analysis (rank 3), its influence on continuance usage intention was significantly lower (rank 4) (Table 10). This suggests that PE contributes more strongly to students' learning value than to their direct continuance usage intention. Even though traditional literature positions PE as one of the strongest predictors of behavioral intention [34], the present findings indicate that usefulness of ChatGPT alone may no longer guarantee continued usage intention.

Table 10. Comparison Between PLS-SEM and ANN results

PLS-SEM Path	Path Coefficient	Normalized Relative Importance (%)	Ranking Based on PLS-SEM	Ranking Based on ANN
PE -> LV	0.263	46.18%	2	3
EE -> LV	0.186	68.76%	3	2
PT -> LV	0.017	17.12%	Insignificant	4
HM -> LV	0.383	100%	1	1
PE -> CI	0.151	33.41%	4	4
EE -> CI	0.055	12.89%	Insignificant	5
PT -> CI	0.158	41.04%	3	2
HM -> CI	0.182	36.20%	2	3
LV -> CI	0.337	100.0%	1	1

Students may initially have been attracted to ChatGPT because of its ability to generate answers quickly (increasing task performance), however, the growing awareness of students using AI-generated content may have increased stricter academic policies and implementation of AI- detection tools by universities that may have altered how students now use ChatGPT. Students are increasingly using ChatGPT to clarify concepts and improve their understanding of the subject therefore

continued usage intention is dependent more strongly on the extent to which students perceive genuine learning value from Gen-AI tools.

Effort expectancy had an 'indirect only' full mediation, where EE had a significant positive effect on learning value, but it did not have a significant relationship with students' continuance intention to use ChatGPT, diverging from several recent studies [13, 15, 17, 19]. However, [12] and [16] also found EE to be non-significant in their studies. One possible explanation is that ease of use functions less as a continuous driver of continuance and more as a threshold and hygiene factor. Once a technology reaches an acceptable level of usability, additional improvements in ease of use may contribute little to users' motivation to continue using it. Current university students who have grown up with technology and who are already familiar with conversational interfaces are also likely to find ChatGPT easy to use and therefore EE as a factor does not actively drive continuance usage intention once the basic usability function has been met.

The ANN findings provide further support for this interpretation. Unlike the linear path model, ANN can capture complex and potentially non-linear relationships between predictors and outcomes. If EE exerted a meaningful threshold and non-linear influence on continuance intention, its predictive importance would still be expected to emerge in the ANN analysis. Instead, EE had the lowest relative importance in predicting CI (12.89%), while ranking second in predicting LV (Table 10). The contrasting predictive importance of EE across the two ANN models provides further evidence that usability operates differently at different stages of the learning process. Ease of use is relatively important in generating perceived learning value because a low effort interface allows students to devote greater attention to exploring concepts and interacting with the system. However, once this basic usability threshold has been met, ease of use contributes little to the decision to continue using ChatGPT. In other words, students are unlikely to continue using ChatGPT simply because it is easy to use, rather they are more likely to do so when that ease of use enables a meaningful and valuable learning experience. This finding provides strong empirical support for viewing EE as a hygiene factor in post-adoption Gen-AI contexts.

The role of perceived trust is interesting as, contrary to expectations, PT did not significantly influence learning value although it emerged as a significant predictor of students' intention to continue using ChatGPT. PT reflects confidence in the accuracy, reliability and credibility of AI generated outputs, whereas LV reflects the educational benefit students perceive from using ChatGPT, such as knowledge acquisition, feedback, and support for the learning process. A response can be reliable without being pedagogically rich, and an imperfect response can be useful if it stimulates further thinking and helps students approach a problem differently.

Students' perception of learning value may arise from interactive learning, regardless of whether they fully trust every output generated by AI. However, trust becomes increasingly important (ranked 2nd in ANN) when students decide whether to continue relying on ChatGPT over time (Table 10). Students who perceive ChatGPT as unreliable may become hesitant to integrate it consistently into the learning process. This confirms the prior findings where trust was found to be a key factor in the adoption and usage of generative AI in educational settings [12]. This reconfirms the existing notion that a student's confidence in the Gen-AI tool will increase when they are confident that the output generated is accurate and reliable. The stronger students' belief in ChatGPT's usefulness, transparency, ethics and reliability; the higher the chances of their long term dependency on it.

However, when trust develops into ‘blind trust’, students may be less inclined to question and verify AI generated responses, including potentially inaccurate, incomplete, or oversimplified information and create a potential risk to the quality of learning [33]. Such uncritical use may reduce opportunities for independent evaluation, reflection, and critical thinking, potentially weakening the learning benefits that students derive from the technology. Over time, therefore, excessive reliance on trusted AI outputs could undermine the very learning value that makes continued use meaningful. Trust should consequently be accompanied by critical evaluation and verification to ensure that continued engagement with ChatGPT remains educationally beneficial.

Hedonic motivation became the strongest predictor of learning value and retained significant influence over continuance usage intention (Table 10). These findings suggest that enjoyment and engagement are meaningful drivers of students using ChatGPT for learning purposes consistent with earlier research such as [15, 17]. These results suggest that when a technological tool such as ChatGPT is enjoyable to use, students may spend more time exploring concepts, asking questions and experimenting with ideas that increase perceived educational value and deeper learning experiences. Prior research supports this view, noting that interactive systems often customize the experience as per the user’s requirements such that it enhances enjoyment and encourages continued use [58].

Lastly, learning value emerged as the most influential determinant of students’ intention to continue using ChatGPT in both PLS-SEM and ANN analysis (Table 10) and is consistent with prior findings [15, 16]. This suggests that students continue to use ChatGPT primarily because they perceive it as beneficial to their learning process. The conversational style of interaction in ChatGPT allows students to ask questions and receive feedback tailored to their learning capacity. This conversational style feature acts as a direct guidance that increases engagement and promotes active learning. This style is very useful for student learning that motivates them to use ChatGPT regularly. The fact that LV has emerged as the strongest predictor establishes that ChatGPT is no longer a tool that simply assists in task completion but rather a technological partner for learning-centered value creation. The mediating role of learning value further strengthens this conclusion.

The combined use of PLS-SEM and ANN offers complementary insights into the determinants of continuance usage intention. While PLS-SEM effectively explains causal relationships, ANN uncovers hidden non-linear relationships. While both approaches identify learning value as the most influential factor, the relative importance of the remaining predictors differs slightly across methods justifying the necessity to integrate linear explanatory models with non-linear predictive methods.

6. Implications

6.1. Theoretical Implications

As the popularity of ChatGPT continues to rise, the findings of this paper become very relevant by contributing to the growing literature. This paper offers several theoretical implications regarding the continuous usage of ChatGPT in an educational environment. By extending the UTAUT framework, this study establishes that learning value plays a crucial role in explaining the usage of generative AI among university students. Therefore, traditional UTAUT factors that primarily focus on usefulness and ease of use alone are insufficient for explaining adoption in Gen-AI contexts, thereby requiring a reconceptualization of the framework. Future studies related to emerging Gen-AI tools should incorporate learning-centered and experience driven factors to account for the distinctive nature of Gen-AI tools.

This study highlights that LV, which refers to students' perception of how a tool supports their overall learning process, is identified as a key determinant of technology adoption. Students are seen to view ChatGPT as a tool that expands their horizon of knowledge rather than just being one that enables them to complete tasks and assignments faster. As learning value is a universal feature of educational technology use, it is expected that learning value will be a significant factor across different cultural and institutional settings. Similarly, hedonic motivation is likely to be a globally relevant enabler in technology usage which suggests that the relationships observed in this study are theoretically transferable to other higher education settings.

Furthermore, this study draws attention to the limited role of performance expectancy, and the non-significant effect of effort expectancy on the continuation usage intention of ChatGPT among university students. These findings challenge the conventional assumptions of technology acceptance theories by showing that the influence of PE and EE is largely indirect and operates through perceived learning value where their direct effect on continuance intention was comparatively weaker. In a mature digital environment, usability becomes a baseline condition, continuance usage depends on whether these translate into meaningful learning value. These results further support the viewpoint that continuance usage of technology is based on factors such as learning value, trust and engagement rather than instrumental efficiency.

A further contribution lies in clarifying the unique role of perceived trust in Gen-AI usages. Despite assuming that trust is an important factor in a learning-centric environment, PT is ranked last in this study when influencing learning value but instantly rises to the second most powerful determinant of final continuance usage intention. Thus trust operates more as a behavioral assurance rather than value enhancer in learning environment.

Finally, this study also provides contributions through the research methodology and design adopted where both PLS-SEM and ANN were combined to understand the technological continuance process better. Both methods combined fill in the gaps created by each; where PLS-SEM seamlessly explains the linear causal relationships between the variables and ANN addressed the non-linear pattern and the relative importance of the predictors. By adding ANN analysis, it has become evident that trust operates in nonlinear ways that are not captured by SEM analysis. Thus depending on traditional linear modelling such as PLS-SEM alone may underestimate the strategic importance of trust in Gen-AI usage. In broader Gen-AI adoption field, the study reinforces the value of adopting hybrid methods where relationships are unlikely to be purely linear.

Based on all of the above, these findings indicate that UTAUT, in its original form, does not fully capture the dynamics of Gen-AI continuance intention. A reconceptualization of UTAUT model by including learning value, trust and hedonic motivation is necessary to understand technology continuance models in AI-mediated learning contexts.

6.2. Practical Implications

This study offers a number of practical and pedagogical implications for both educators and Gen-AI developers alike. For educators, ChatGPT should be considered as a learning-enhancement tool that supports students' academic development. Educators therefore need to design curricula where Gen-AI tools can be applied at a more critical level rather than just as a task completion tool. Rather than simply looking for answers from ChatGPT, students should know how to ask the right questions, evaluate AI-generated responses, discuss limitations and provide prompts that further strengthen conceptual learning and academic knowledge. Using ChatGPT in more exploratory ways

that support explanation, feedback and iterative understanding can enhance learning value and academic engagement while mitigating the risks of passive reliance.

To further reduce the risk of passive reliance and blind trust, educators can incorporate prompt engineering training and AI fact-verification protocols into coursework. For instance, universities could provide structured training in prompt engineering, teaching students how to pose more specific and iterative queries rather than single questions. This should be complemented by explicit AI fact-verification practices that require students to cross-check ChatGPT's output against course material before it is used in coursework. Students can also be required to document how they formulated prompts, cross-check important factual claims against authoritative sources, identify inconsistencies in AI-generated responses, and explain why particular outputs are accepted, modified, or rejected. Embedding these verification practices into formal instruction can encourage more active and critical engagement with Gen-AI tools while ensuring that students retain responsibility for evaluating the accuracy and quality of their outputs.

For Gen-AI developers and policymakers looking to implement ChatGPT in educational settings, the role of trust in responsible Gen-AI use deserves equal attention. The significant effect of perceived trust on continuance intention indicates that ChatGPT must ensure transparency, reliability and ethical conformance in the generated outputs. Introducing real-time 'confidence score' can overcome algorithmic hallucinations and build confidence. The inclusion of such factors along with an interactive interface will support sustained and responsible use of the platform. Additionally, policymakers and those involved in academic administration must ensure that institutional guidelines are effectively designed and communicated such that the use of Gen-AI tools is responsible and within the parameters of academic integrity.

Finally, the positive influence of hedonic motivation on both learning value and continuance usage intention of university students implies that developers must take the steps needed to make such technological tools interactive and engaging for users. The improvement of user experience with an engaging interface is likely to make Gen-AI tools like ChatGPT the learning partner of university students into the foreseeable future as well.

6.3. Limitations and Future Research

The contributions of this paper form a strong foundation which future research can build upon. As the study was conducted in Bangladesh, future research can enhance the scope and validity of this model by comparing the results of different national, cultural and institutional settings. This will help to determine the extent to which learning value and hedonic motivation operate as universal versus context-specific drivers of Gen-AI technology usage. Furthermore, given the rate at which technology such as Gen-AI is evolving in the present day, it is a matter of time before students' perceptions, expectations and usage patterns would change. This indicates the potential for longitudinal research designs in the future that capture the differences in technological usage behavior over a period of time. Moreover, using actual academic progress reports can help examine whether learning value translates into improved academic performance over time.

There is also significant scope for future research in the exploration of ethical, regulatory and pedagogical factors that drive the usage and adoption of Gen-AI tools among university students. The extent to which students have become over-dependent on Gen-AI tools such as ChatGPT has raised concerns among many educators, as it has resulted in varying levels of academic misconduct and lack of originality. The over-reliance on such technological tools can be seen as detrimental to

student creativity; thereby hampering their ability to comprehensively acquire and develop their knowledge while at university. Future research should measure AI over-reliance using indicators such as uncritical acceptance of AI outputs, frequency of accepting AI-generated answers without verification, reduced independent problem solving, or dependence on AI for tasks that students could reasonably complete independently. Combining self-reported measures with actual usage logs or task-based experiments would provide a more rigorous assessment of the potential consequences of excessive reliance on Gen-AI tools.

7. Conclusions

This study examined the factors that influence university students' continuance usage intention toward ChatGPT, shifting the focus from initial technology adoption to post-adoption retention. A modified UTAUT framework and a hybrid PLS-SEM and ANN approach were adopted to examine these relationships. Based on data from 351 university students, the results indicated that learning value was the strongest predictor of continuance usage intention, followed by hedonic motivation, perceived trust, and performance expectancy. Effort expectancy, however, did not significantly influence continuance usage intention.

Theoretically, extending the UTAUT framework with learning value as a mediator and perceived trust and hedonic motivation as additional antecedents offers a more complete explanation of Gen-AI continuance in higher education. Methodologically, combining PLS-SEM and ANN provides complementary explanatory and predictive insights into the linear and non-linear relationships among the variables. Contextually, the study addresses a notable gap in the literature by providing evidence from a developing-country context.

The practical implications of this study suggest that educators should consider ChatGPT as a learning-enhancement tool and therefore should design assessments where students can critically engage with the tool. Similarly, AI developers, while developing Gen-AI educational tools, should consider the importance of transparency and accuracy of generated outputs to build students' trust in these tools. Given the growing use of ChatGPT, this study offers a timely insight for theory, practice and policy upon which future research on the role and importance of educational Gen-AI tools can be based.

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