Understanding AI-Assisted Learning Acceptance among Vocational Students: An AIDUA Model Approach

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***Abstract*—This study addresses a significant gap in the empirical research on Artificial Intelligence (AI) acceptance in education by introducing AI hallucinations as a pivotal, underexplored factor. Grounded in the AI Device Use Acceptance (AIDUA) model, our research extends the framework to investigate how AI hallucinations, alongside anthropomorphism, influence students' acceptance process. This study employed a convenience sampling strategy to survey students from Chinese vocational colleges with prior AI experience. A hypothetical model was constructed across the three stages of the AIDUA framework (primary appraisal, secondary appraisal, and outcome stage), and was validated using Structural Equation Modeling (SEM). The results demonstrate that AI anthropomorphism and AI-generated hallucinations act as key antecedents in the primary appraisal stage. These factors are subsequently linked to AI use anxiety and trust during the secondary appraisal. Ultimately, anxiety and trust significantly correlate with satisfaction and the intention to continue using AI. The model showed strong explanatory power, with all 11 hypotheses supported and an R^2 of 0.76 for continued use intention, underscoring the critical role of the included variables. The primary theoretical contribution is the formal integration of AI hallucinations into the AIDUA model. Practically, this insight aids educators and developers in enhancing AI implementation by mitigating factors that erode trust and satisfaction.**

***Keywords*—Artificial Intelligence Device Use Acceptance (AIDUA) model, anthropomorphism, Artificial Intelligence Generated Content (AIGC), continued intention, hallucinations, satisfaction, trust, use anxiety**

I. Introduction

Since the launch of ChatGPT in November 2022, the rapid proliferation of Artificial Intelligence Generated Content (AIGC) products has significantly increased public engagement with AI. In educational settings, AIGC supports learners by facilitating tasks such as information retrieval, answering queries, providing prompts, planning, summarizing, refining, analyzing, and generating content [1]. However, despite its widespread use, the majority of users are still navigating AI usage. Therefore, this study examined how AI anthropomorphism, hallucinations, trust, and anxiety predict satisfaction and continued use of AI-assisted learning.

Human-machine interaction is a complex process during which a number of different factors affect whether an individual accepts AI technologies in their daily life [2]. Studies from around the world have shown that AI is perceived to be both a risk and an opportunity [3]. However, there is little empirical evidence of how specific AI attributes, and in particular challenges such as AI hallucinations, impact the acceptance of AI in educational contexts. While AI has powerful implications for learning, it is essential to gain a deeper understanding of the factors that both drive and hinder its acceptance by students. With a focus on AI-assisted learning, this study investigated students' acceptance process by incorporating AI hallucinations as a central factor that has, as yet, been unexplored.

Research on user acceptance is crucial for guiding the development and refinement of AI applications [4]. Unlike previous technologies, AI presents exceptional potential, but its actual usage often varies significantly. Current research on users' intentions to adopt AI technologies typically relies on established Technology Acceptance Models (TAM) [5], which were originally designed for non-intelligent technologies, and do not fully account for the unique attributes of AI [6]. To address this gap, Gursoy *et al.* [5] proposed the AI Device Use Acceptance (AIDUA) model, comprising three stages. This model outlines a progressive process whereby accumulating knowledge about AI can lead to either confidence in or rejection of AI usage [2]. According to Yang *et al.* [6], users' comprehensive cognitive assessments, based on their perceptions of specific AI characteristics, drive their willingness to use AI, as further supported by Venkatesh [7]. This study, therefore, sought to explore the interrelations among variables relevant to students' acceptance of AI-assisted learning.

Smart manufacturing and digital transformation are powerfully driving the development and transformation of vocational education and training, and is accelerating the high-quality development of higher vocational education [8]. Vocational college students were specifically chosen as the subjects of this investigation as they are an ideal population for examining AI acceptance due to their position at the forefront of integrating AI into both learning and practical skill development. In this study, we therefore explored the interrelations among variables relevant to these specific students' acceptance of AI-assisted learning.

Anthropomorphism, a key characteristic of AI technology that enhances user engagement with AIGC products, has been posited to influence acceptance levels. Anthropomorphism is integrated as a predictive variable for

user acceptance in the AIDUA model [9]. Accordingly, this study incorporated it as an important antecedent in the AI acceptance framework. Trust, a foundational aspect of user behavior, is widely regarded as being crucial for predicting behavioral intentions to use AI [4, 10]. Given its established relevance, trust was also included as a key variable in the proposed model.

Technical concerns primarily encompass perceived performance anxiety and communication barriers [11]. The apprehension over losing control of novel technologies often outweighs their potential benefits [12], and AI-related anxiety reflects such control concerns. Moreover, AI systems are susceptible to errors and non-transparent feedback mechanisms due to limitations in input-output processing, frequently resulting in nonsensical outputs, a phenomenon known as AI hallucinations. These hallucinations represent an emerging yet underexplored factor that may critically influence user acceptance, trust, and satisfaction. Therefore, this study incorporated both AI use anxiety and AI hallucinations into the research model.

Performance measurement plays a decisive role in determining the effectiveness of human-machine systems in accomplishing technologically designed tasks [13]. Well-designed AI systems that address user concerns and deliver timely responses can enhance service quality, improve satisfaction, and encourage sustained usage [14]. Conversely, user dissatisfaction may inhibit continued engagement. Thus, this study integrated AI use satisfaction into the acceptance model to examine its relationship with continuance intention.

To sum up, this study examined vocational college students' AI-assisted learning acceptance process, focusing specifically on AI hallucinations as the main conceptual gap. By clarifying how these students perceive and interact with AI, especially in those contexts where hallucinations could undermine trust and satisfaction, this study sought to provide educators and AI developers with actionable insights that can support more effective AI implementation in educational environments.

II. Theoretical Foundation, Hypotheses, and Model

A. The AIDUA Model

Gursoy *et al.*'s [5] AI Device Use Acceptance (AIDUA) model comprises a three-step acceptance generation process, namely the primary appraisal, secondary appraisal, and outcome stage, whereby users form their acceptance of AI devices. In the primary appraisal stage, users assess whether AI technologies align with their needs, a crucial step that determines their progression to the secondary appraisal stage. The application of the AIDUA model is particularly significant because it enables meaningful cognitive and affective evaluations of AI tools, assuming a basic understanding of digital technology [15]. According to the model's perspective, individuals tend to minimize dissonance by adhering to prior evaluations rather than challenging them. Consequently, customers who develop positive attitudes toward AI devices during the primary evaluation phase often affirm existing evaluations during secondary assessments, and vice versa [5]. In other words, users evaluate the benefits and develop emotional responses regarding the use of AI devices, which ultimately influence their willingness to use these technologies in the outcome stage [9], as depicted in Fig. 1 and Table 1. The AIDUA model thus serves as a comprehensive framework for understanding the sequential decision-making process users undergo, capturing both cognitive evaluations and emotional reactions throughout the service interaction. This model has been applied across various studies to elucidate the psychological mechanisms underpinning consumer acceptance of AI-based services [16].

The current study posited that the AIDUA model offers a flexible interpretive framework, allowing relevant variables to be effectively aligned with its three stages. Leveraging the AIDUA model's structured approach, this study aimed to investigate how AI anthropomorphism, AI hallucinations, AI use anxiety, AI trust, AI use satisfaction, and continued intention to use AI are interconnected.

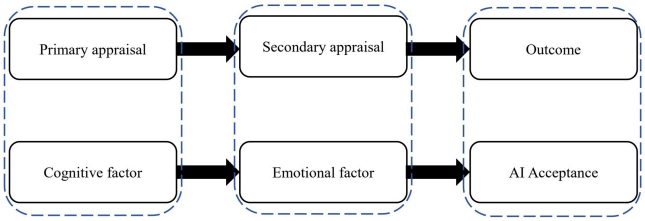

Fig. 1. AIDUA model concept.

B. Research Hypotheses

Existing technology acceptance models such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) primarily focus on functional and non-intelligent technologies [17], with none directly addressing the acceptance of artificial intelligence [15]. Therefore, a comprehensive model is needed to map the psychological pathway that leads customers to willingly accept the use of AI-powered devices during service interactions [5]. In the AIDUA model, the primary appraisal involves a preliminary evaluation of the importance and relevance of AI devices in service interactions [18]. This first stage of acceptance generation enables consumers to determine whether AI use aligns with their values and expectations [9]. A key concern is whether AI can match or exceed human service levels, with a positive user experience fostering trust in the technology [5, 13]. The anthropomorphization of artificial intelligence has been found to have positive effects [19]. However, a notable challenge with generative AI is its propensity for "AI hallucinations", that is, producing plausible but incorrect information, which, coupled with anthropomorphic designs, may lead to misplaced trust in the AI's output [20].

Additionally, anthropomorphism has been posited to raise users' expectations of AI performance, correlating with positive emotional responses as AI's human-like qualities increase [18, 21]. This expected performance, if unmet, particularly when AI generates coherent but false responses, could lead to reduced trust and increased user anxiety. As such, it can be inferred that as the level of AI anthropomorphism increases, users' expectations of AI performance will increase, making them more likely to notice AI's nonsensical or erroneous responses. Conversely, a

higher degree of anthropomorphism tends to reduce user anxiety and foster greater trust in the technology. Based on these insights, the research hypotheses are as follows:

H1: AI anthropomorphism is positively correlated with AI hallucinations.

H2: AI anthropomorphism is negatively correlated with AI use anxiety.

H3: AI anthropomorphism is positively correlated with AI trust.

Although AI mimics human intelligence and requires no learning to operate, the issue of hallucinated outputs remains a significant concern. While these outputs may sound plausible, there is often no reliable way to verify their accuracy, necessitating caution [20]. For example, many have observed how ChatGPT can generate "hallucinations", which may influence users' perceptions of its quality and reliability [22]. Despite efforts to improve generative AI safety through human feedback, biases continue to persist [23], potentially undermining users' trust in the technology.

Furthermore, the use of technology often brings about undesirable side effects, such as strong negative emotional responses during human-computer interactions [24]. From a cognitive-affective-regulation perspective, Zhou and Zhang [25] suggested that informational hallucinations can lead to cognitive dissonance, resulting in intermittent disengagement, a passive behavior that can lead to user attrition and hinder the ongoing development of generative AI. In this context, negative outcomes are likely to trigger technological anxiety, characterized by users' feelings of anxiety and fear during their interactions with AI systems [21]. This aligns with Cognitive Dissonance Theory (CDT), which posits that the psychological discomfort experienced when individuals encounter inconsistencies between cognitions and behaviors is inherently emotionally unsettling [26]. Therefore, it can be inferred that the more frequently AI produces erroneous responses, the higher the users' anxiety, and the lower their trust in the technology. The following hypotheses were therefore proposed:

H4: AI hallucination is positively correlated with AI use anxiety.

H5: AI hallucination is negatively correlated with AI trust.

In the secondary appraisal, individuals predominantly assess their options and potential outcomes from an emotional perspective [5]. The perceived value of AI tools hinges on a balance between potential benefits and risks, with the value increasing when the benefits surpass the risks [11]. Both supporting and opposing factors can coexist and interact, shaping users' acceptance behaviors [5]. Clearly, people's perceptions of AI affect their adoption of the technology [12]. From the theoretical perspective of perceived risk, individuals are easily undermined by perceived threats, and exhibit fragile overall trust in the media [27]. It has been demonstrated that high perceived risk diminishes trust and subsequent usage. Only when people understand new technologies and are less likely to worry about them are they more likely to adopt them [28]. Therefore, AI acceptance involves a cognitive evaluation process, where users assess the necessity of AI devices by considering the psychological effort required to interact with the technology. Negative emotions, such as anxiety, can result in resistance to using these devices [29]. Technological anxiety has been found to negatively impact the relationship between attitudes toward technology and the intention to use it [21]. This study drew on CDT, which suggests that users experiencing emotional reactions will avoid unpleasant information to reduce psychological discomfort [26, 30]. Specifically, individuals with anxiety tend to focus more on negative outcomes and make decisions that prioritize avoiding potential risks [31]. Furthermore, research indicates that internet security anxiety significantly undermines internet trust [32]. Therefore, it can be inferred that the greater the anxiety surrounding AI usage, the lower the trust in the technology, ultimately reducing user satisfaction and willingness to continue using AI for learning. Accordingly, the following hypotheses were proposed:

H6: AI use anxiety is negatively correlated with AI trust.

H7: AI use anxiety is negatively correlated with AI use satisfaction.

H8: AI use anxiety is negatively correlated with the intention to continue using AI.

In the outcome stage, consumers' emotional responses to AI devices influence their behavioral intentions [16], with trust being a critical factor in enhancing user satisfaction and encouraging continued use. Internet trust significantly shapes customer perceptions [32], and studies have demonstrated that user satisfaction is closely tied to their trust in system services [33]. For instance, research has shown that trust in AI directly impacts satisfaction with AI-based services, such as chatbots [34]. Positive emotions foster favorable outcomes, such as the willingness to adopt AI devices [9]. In particular, these emotions can drive users' intentions to embrace AI technology [29]. As user trust in AI increases, so does their confidence in the tool's capabilities, which further reinforces their intention to continue using these tools [4]. Thus, it can be inferred that higher levels of trust in AI lead to greater satisfaction with the technology, as well as a stronger willingness to continue using AI to support learning. The following hypotheses were therefore proposed:

H9: AI trust is positively correlated with AI use satisfaction.

H10: AI trust is positively correlated with the intention to continue using AI.

User experience is commonly regarded as one of the individual difference factors that shape users' perceptions of system usage [24]. When users have a positive experience with a chatbot, their satisfaction increases, making them more likely to continue using it [14]. This suggests that, in most cases, direct or past experiences with a system positively influence users' engagement [24]. Additionally, research shows that decisions to continue using a service are often based on past experiences, with users weighing the benefits against the costs, underscoring the critical role of satisfaction [33]. Consequently, the higher a user's satisfaction with AI technology, the more likely they are to continue using it to support their learning. The corresponding hypothesis is as follows:

H11: AI use satisfaction is positively correlated with the intention to continue using AI.

Table 1 summarizes the study's 11 hypotheses and the expected directions of each path.

Table 1. Research hypothesis summary table

No.	Path	Expected direction
H1	AI anthropomorphism→AI hallucinations	Positive
H2	AI anthropomorphism→AI use anxiety	Negative
H3	AI anthropomorphism→AI trust	Positive
H4	AI hallucinations→AI use anxiety	Positive
H5	AI hallucinations→AI trust	Negative
H6	AI use anxiety→AI trust	Negative
H7	AI use anxiety→AI use satisfaction	Negative
H8	AI use anxiety→intention to continue using AI	Negative
H9	AI trust→AI use satisfaction	Positive
H10	AI trust→intention to continue using AI	Positive
H11	AI use satisfaction→intention to continue using AI	Positive

C. Research Model

Past research findings have confirmed that the AIDUA model can be used to explore AI acceptance in educational settings and to assess the cognitive and affective structuring processes among student groups. Building on the AIDUA model and the structured framework of three acceptance generation stages, primary appraisal, secondary appraisal, and outcome stage, this study structured the logical relationships among six key variables. The model situates AI anthropomorphism and AI hallucinations within the primary appraisal stage, AI use anxiety and AI trust within the secondary appraisal stage, and AI use satisfaction along with continued intention to use AI in the outcome stage. From this structure, a research hypothesis model featuring 11 hypothetical paths was developed to investigate the significant associations among these variables (as depicted in Fig. 2).

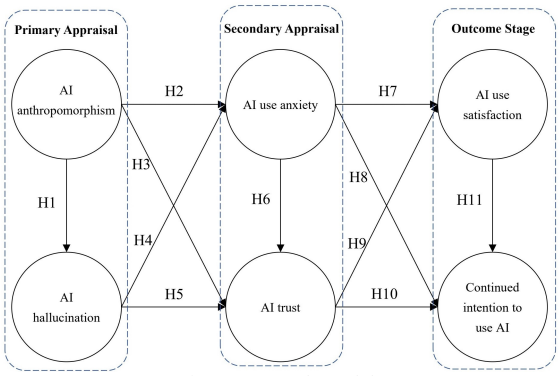

Fig. 2. Research model.

III. Research Design

A. Procedure and Participants

This study employed a questionnaire-based approach, distributing surveys via the Wenjuanxing platform in September 2024. A convenience sampling strategy was adopted to efficiently target the specific population of Chinese vocational college students with prior experience of AI-assisted learning. While this method is pragmatically justified for initial model validation within this defined educational context, its limitations regarding generalizability are acknowledged. Teachers assisted in disseminating the survey link and invitation statements to their students. The introductory page detailed the study's purpose, data usage, participants' rights, and contact information. Participants were first screened for prior AI-assisted learning experience; only those with experience proceeded to complete the questionnaire.

The initial data collection yielded responses from 1,200 participants. However, after discarding 141 questionnaires due to rapid completion times (under 2 minutes) or incomplete answers, the number of valid responses was narrowed down to 1,059, resulting in an effective recovery rate of 88.2%. The effective sample size in this study exceeded the minimum sample size of 200 recommended by Weston *et al.* [35] for any Structural Equation Modeling (SEM). The average age of participants was 19.58 years, with a standard deviation of 1.453 years. The distribution of participant characteristics is detailed in Table 2.

Table 2. Basic information

Variable	Category	Frequency	Percentage
Gender	Male	642	60.6
	Female	417	39.4
School Affiliation	Public	733	69.2
	Private	326	30.8
	Higher Vocational Colleges	608	57.4
	Vocational and Technical University	451	42.6
Professional Field	Liberal Arts	281	26.5
	Engineering	387	36.5
	Agriculture	130	12.3
	Business	216	20.4
	Other	45	4.2
Frequency of Using AI for Learning	At least once a day	187	17.7
	Two to five times a week	597	56.4
	Less than twice a week	275	26
Most Frequently Used AI System	ChatGPT	177	16.7
	Kimi AI	405	38.2
	Wenxin Yiyan (文心一言)	296	28
	iFlytek Zhiwen (讯飞智文)	113	10.7
	Other	68	6.4
Purpose of Use	Information Inquiry	412	38.9
	Problem Discussion	144	13.6
	Text Refinement	318	30
	Document Processing	110	10.4
	Other	75	7.1

B. Questionnaire

A confirmatory approach based on self-assessment reports was adopted in this study to understand students' AI acceptance and usage. The questionnaire was developed with reference to the literature and to theories relevant to the use of AI in educational settings. To ensure that the items were linguistically and culturally appropriate for the Chinese respondents, rigorous translation and back-translation of the original English scales were undertaken, including an initial forward translation by a bilingual expert, and an independent back-translation by another translator. Discrepancies were examined and resolved by the research team in order to ensure conceptual equivalence. After initial drafting, the questionnaire was reviewed by three educational technology experts with doctoral degrees, and was then refined. A 5-point Likert scale, from 1 (strongly disagree) to 5 (strongly agree), was used. The complete questionnaire is provided in the Appendix.

1) AI anthropomorphism

AI anthropomorphism refers to users' perception that AI exhibits human-like characteristics, responses, or behaviors. This study adapted the anthropomorphism scale from Wang [36], which consisted of seven items, to measure participants' perceptions of AI's human-like qualities, as shown in the Appendix.

2) AI hallucinations

AI Hallucinations measure the occurrence of AI responses

that are coherent but erroneous, and which lack meaningful content or logic. A 7-item scale was developed for this study to gauge users' frequency and perception of these occurrences. A rigorous expert review process was undertaken to ensure the content validity of the scale. Three educational technology and AI domain experts were invited to evaluate the items to ensure their clarity and relevance, and the representativeness of the construct. Wording was refined and the item pool was finalized based on their feedback. The items are shown in the Appendix.

3) AI trust

This dimension assesses the perceived reliability of AI technologies. Leveraging a modified version of Ejdys's technology trust scale [37], which consists of seven items, this measure captures participants' trust in the accuracy and dependability of AI-provided content, as shown in the Appendix.

4) AI use anxiety

AI use anxiety reflects the discomfort or apprehension experienced while interacting with AI. The scale, reworked from Hong *et al.*'s [38] technology anxiety scale and consisting of five items, aims to quantify the level of anxiety users feel when using AI technology, as shown in the Appendix.

5) AI use satisfaction

Evaluating users' satisfaction with their AI experiences, this scale was adapted from Wang *et al.*'s [39] learning satisfaction scale. With eight items, it measures the extent to which AI tools meet the educational needs and expectations of student users, as shown in the Appendix.

6) Continued intention to use AI

This construct explores the long-term willingness of users to continue utilizing AI for learning assistance. Adapted from Hong *et al.*'s [40] continued intention scale, it comprises six items designed to measure the sustained engagement users foresee with AI technologies, as shown in the Appendix.

Before proceeding to hypothesis testing, it was critical to confirm the reliability and validity of the scales [41]. This study reports Cronbach's α and Composite Reliability (CR) values ranging from 0.86 to 0.94, surpassing the recommended threshold of 0.70, indicating excellent internal consistency [42]. Average Variance Extracted (AVE) and Factor Loadings (FL) followed standard thresholds. Specifically, FL and AVE values ranged from 0.74 to 0.85 and 0.55 to 0.73, respectively, each exceeding the 0.50 benchmark, thereby confirming the constructs' convergent validity, as presented in Table 3. The reliability and validity of the questionnaire used in this study met the standards proposed by Hair *et al.* [42].

Table 3. Reliability and validity analysis

Construct	Items	*M*	*SD*	*α*>0.7	*CR*>0.7	*AVE*>0.5	*FL*>0.5
AI Anthropomorphism	5	3.78	0.67	0.86	0.86	0.55	0.74
AI Hallucinations	6	3.27	0.96	0.90	0.90	0.61	0.78
AI Use Anxiety	4	3.15	1.09	0.88	0.88	0.65	0.81
AI Trust	5	3.68	0.81	0.86	0.86	0.55	0.74
AI Use Satisfaction	6	3.76	0.90	0.94	0.94	0.73	0.85
Continued Intention to Use AI	5	3.81	0.89	0.88	0.88	0.60	0.78

*Note: FL = average standardized factor loading

C. Statistical Methods

Structural Equation Modeling (SEM) is a robust analytical technique prevalent in the social and behavioral sciences, particularly for testing complex relationships within research hypotheses [43]. This method adeptly manages multiple layers of variable interactions, enabling researchers to assess both direct and indirect effects among exogenous and endogenous variables. Consequently, upon verifying the reliability and validity of the measurement instruments, this study implemented confirmatory factor analysis to construct the models, and employed SEM for subsequent analyses.

IV. Results and Discussion

A. Common Method Bias (CMB)

According to Podsakoff *et al.* [44], in exploratory factor analysis, CMB exists if the first factor accounts for over 50% of the variance. In this study, Harman's single-factor method was used to examine CMB, yielding six factors which explained 69.61% of the cumulative variance, with the first factor accounting for 10.58%. Thus, there was no significant CMB in this study.

B. Skewness and Kurtosis Analysis

Kline stated that when the critical value for skewness is less than 3 and the critical value for kurtosis is less than 10 [45], a univariate normal distribution of the data is assumed. As shown in Table 4, in this study, the skewness ranged from −0.48 to −1.25 and the kurtosis ranged from −1.22 to 1.88, indicating that all variables exhibited a normal distribution.

Table 4. Skewness kurtosis analysis

Construct	Skewness	Kurtosis
Threshold value	< ±3	< ±10
AI Anthropomorphism	−0.94	1.12
AI Hallucinations	−0.48	−0.79
AI Use Anxiety	−0.20	−1.22
AI Trust	−1.25	1.88
AI Use Satisfaction	−1.13	1.60
Continued Intention to Use AI	−1.20	1.78

C. Measurement Model Analysis

Table 5. First-order confirmatory factor analysis

Construct	χ^2	*df*	χ^2/df	RMSEA	GFI	AGFI
AI Anthropomorphism	14.17	5	2.83	0.04	0.99	0.98
AI Hallucinations	18.17	9	2.02	0.03	0.99	0.99
AI Use Anxiety	4.51	2	2.26	0.03	0.99	0.99
AI Trust	8.44	5	1.69	0.03	0.99	0.99
AI Use Satisfaction	37.01	9	4.11	0.05	0.99	0.98
Continued Intention to Use AI	6.89	5	1.38	0.02	0.99	0.99

The initial assessment of the measurement model's fit to the data established the foundational requirements for convergent validity. Each indicator was evaluated to ensure that it sufficiently converged on its respective construct, an essential criterion for model validity [41]. According to established guidelines by Hair *et al.* [42] and Kenny *et al.* [46], fit indices such as χ^2/df should ideally not exceed 5, RMSEA should be below 0.10, and both GFI and AGFI should exceed 0.80. As part of the model refinement process, items with factor loadings below 0.50 were considered for removal to enhance model validity and reliability. Consequently, adjustments were made resulting in

the retention of five items for AI anthropomorphism, six for AI hallucinations, four for AI use anxiety, five for AI trust, six for AI use satisfaction, and five for continued intention to use AI, as shown in Table 5.

D. Discriminant Validity Analysis

To establish discriminant validity, the Fornell-Larcker criterion was employed, which asserts that the square root of the AVE for each construct should exceed the inter-construct correlation coefficients, as detailed in Table 6. The results validated discriminant validity across all constructs.

Table 6. Discriminant validity analysis

Construct	1	2	3	4	5	6
1. AI Anthropomorphism	(0.74)					
2. AI Hallucinations	0.34	(0.78)				
3. AI Use Anxiety	0.14	0.66	(0.80)			
4. AI Trust	0.27	–0.19	–0.28	(0.74)		
5. AI Use Satisfaction	0.32	–0.17	–0.35	0.73	(0.85)	
6. Continued Intention to Use AI	0.34	–0.18	–0.39	0.66	0.78	(0.76)

*Note: The values on the diagonal are the square root of AVE; other values are correlation coefficients.

E. Model Fit Analysis

The model's fit to the data was assessed using a range of indices, with the results showing $\chi^2 = 819.41$, $df = 423$, $\chi^2/df = 1.94$, RMSEA = 0.03, GFI = 0.95, AGFI = 0.94, NFI = 0.96, NNFI (also known as TLI) = 0.98, CFI = 0.98, IFI = 0.98, RFI = 0.96, PNFI = 0.88, and PGFI = 0.81. These values are well within the acceptable limits proposed by Hair *et al.* [42] and Kenny *et al*. [46], indicating a good fit.

F. SEM Analysis Results

All 11 hypothesized paths in the research model were supported by the Structural Equation Modeling (SEM) analysis (see Fig. 3 and Table 7), with several key patterns revealed: AI anthropomorphism was a significant antecedent which demonstrated a substantial positive relationship with AI trust. There was a particularly strong positive association between AI hallucinations and AI use anxiety, thus showing their role as a major stressor. In the outcome stages of the model, AI trust was shown to be a powerful positive predictor of AI use satisfaction and continued use intention, with a notably strong path from trust to satisfaction. In contrast, AI use anxiety showed consistent significant negative effects throughout the model.

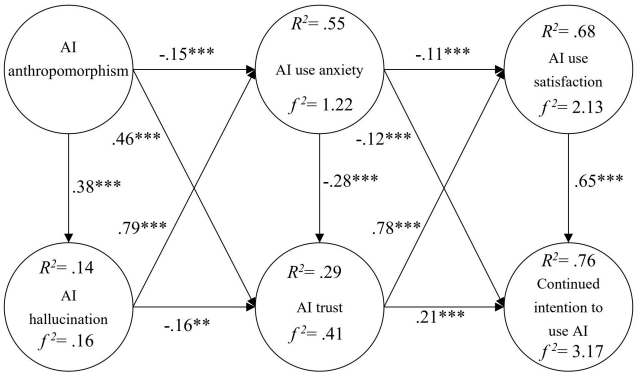

Fig. 3. Study model (Note: *** typically indicates $p < 0.001$, ** typically indicates $p < 0.01$).

The structural model assessment also showed the explanatory power and effect sizes of key constructs. AI anthropomorphism explained 14% of the variance in AI hallucinations ($f^2 = 0.16$), with a moderate effect. AI anthropomorphism and AI hallucinations together explained 55% of the variance in AI use anxiety ($f^2 = 1.22$), with a very large effect. AI anthropomorphism, AI hallucinations, and AI use anxiety together accounted for 29% of the variance in AI trust ($f^2 = 0.41$), indicating that these predictors had a large effect. Moreover, AI use anxiety and AI trust explained 68% of the variance in AI use satisfaction ($f^2 = 2.13$), with a very large effect, while AI use anxiety, AI trust, and AI use satisfaction together explained 76% of the variance in continued intention to use AI ($f^2 = 3.17$), with a particularly large effect that indicates the strong predictive power of the final outcome in the model.

Table 7. Summary of hypothesis verification results

No.	Path	β	Direction	Outcome
H1	AI anthropomorphism→AI hallucinations	0.38***	Positive	Supported
H2	AI anthropomorphism→AI use anxiety	–0.15***	Negative	Supported
H3	AI anthropomorphism→AI trust	0.46***	Positive	Supported
H4	AI hallucinations→AI use anxiety	0.79***	Positive	Supported
H5	AI hallucinations→AI trust	–0.16**	Negative	Supported
H6	H6: AI use anxiety→AI trust	–0.28***	Negative	Supported
H7	AI use anxiety→AI use satisfaction	–0.11***	Negative	Supported
H8	AI use anxiety→intention to continue using AI	–0.12***	Negative	Supported
H9	AI trust→AI use satisfaction	0.78***	Positive	Supported
H10	AI trust→intention to continue using AI	0.21***	Positive	Supported
H11	AI use satisfaction→intention to continue using AI	0.65***	Positive	Supported

Note: *** typically indicates $p < 0.001$, ** typically indicates $p < 0.01$

V. Discussion

A. AI Anthropomorphism is Positively Correlated with AI Hallucinations and Trust, but Negatively Correlated with Use Anxiety

Anthropomorphism refers to attributing unique human psychological characteristics to non-human animals and objects, illustrating humans' tendency to extend social cognition beyond typical social targets [47]. If individuals believe computers are inherently human, that is, if they anthropomorphize computers, then appropriate human responses to computers reflect a reasonable application of social norms and behaviors [48]. For instance, embodied computer agents function as genuine social actors in the truest sense of the word "social", and are capable of establishing relationships with users akin to those in human-to-human interactions [49]. The research findings indicated a positive correlation between AI anthropomorphism and both AI hallucinations and AI trust, alongside a negative correlation with AI use anxiety. These outcomes corroborate previous studies, suggesting that a higher level of perceived anthropomorphism in AI may enhance users' ability to recognize incorrect AI responses that are presented convincingly. Conversely, as AI tools exhibit more human-like responses, user anxiety associated with these tools diminishes, while trust concurrently increases. This is because even when explicitly aware and acknowledging that computers are neither human nor deserving human-like treatment, social responses to computers still occur [50]. Cintamür noted that increased

anthropomorphic features in robots are linked to more positive emotional responses from users, which naturally diminish anxiety [21]. This observation supports Ma and Huo's [18] view that anthropomorphism significantly affects users' evaluations of performance and their expectations of effort. However, Dodgson [20] offered a critical perspective, cautioning that anthropomorphism may make users more susceptible to deception, leading to an uncritical acceptance of information provided by AI.

B. AI Hallucinations are Positively Correlated with AI Use Anxiety, but Negatively Correlated with AI Trust

Trust is a defining characteristic of most economic and social interactions involving uncertainty; indeed, all interactions require an element of trust [51]. If a chatbot is perceived as being highly capable, exchange-oriented users are more likely to increase their trust in it [52]. However, a study on a medical application found hallucinations in AI-generated recommendations involving the production of fictitious information [53]. This finding is also consistent with the results of the present study, namely that AI hallucinations are positively correlated with increased user anxiety and negatively impact user trust. This indicates that when users encounter AI outputs that are consistently incorrect yet are presented convincingly, it not only raises concerns about the tool's reliability, but also diminishes confidence in its usefulness. ChatGPT and similar platforms have been noted for producing such "hallucinations" during content generation, potentially skewing users' perceptions of AI reliability [22]. These errors can critically influence user trust as expectations for accurate and logical output are unmet. Cintamür [21] suggested that the negative outcomes associated with unreliable AI outputs trigger user anxiety, particularly in contexts where dependable performance is critical. The AI Knowledge-Attitude-Practice (KAP) framework proposed by Sanchez *et al.* [54] suggests that users' knowledge and attitudes toward artificial intelligence may influence their levels of trust and anxiety.

C. AI Use Anxiety Is Negatively Correlated with AI Trust, Satisfaction, and Intention to Continue Using AI

Individuals' perceptions of and attitudes toward adopting artificial intelligence may be influenced by their prior technical experience, particularly if they have previously used AI tools or similar educational technologies [55]. The study findings indicate that AI usage anxiety negatively correlates with AI trust, AI usage satisfaction, and willingness to continue using AI. In other words, higher anxiety levels during AI technology use correlate with lower satisfaction and trust in the technology, consequently reducing the willingness to continue using it. These findings resonate with Roy *et al.* [29] who proposed that negative emotions may prompt opposition to using AI devices. This further confirms how people's perceptions of AI profoundly influence its acceptance and willingness to use it. Additionally, Giudice *et al*. [12] emphasized this point, noting that users' perceptions of AI are a key factor affecting their adoption behavior. Similarly, Ouyang [32] found that security anxiety in internet usage negatively impacts users' trust in the internet, aligning with our findings on AI usage anxiety. Cintamür [21] also indicates that technological anxiety negatively affects attitudes toward technology and usage intentions, further supporting anxiety's crucial role in Artificial Intelligence (AI).

D. AI Trust Level Positively Correlates with Satisfaction and Continued Intention to Use AI

Trust is one of the determinants of perceived usefulness [51], and the low acceptance of chatbots is largely attributed to consumers' distrust of them [52]. The research indicated that the level of trust users place in AI positively correlates with both their satisfaction and their intention to continue using AI tools. In other words, as users' trust in AI increases, so does their satisfaction with the technology, leading to a higher likelihood of continued usage. These findings are consistent with prior studies by Roy *et al*. [9], Yoon and Lee [16], and Vitezić and Perić [29], which highlighted how positive emotions play a crucial role in encouraging the adoption of AI technologies. Similarly, our study aligns with Huang *et al.* [34] who demonstrated that trust in AI significantly impacts user satisfaction with chatbots. This aligns with the perspective proposed by Kang *et al*. [56] that trust is a significant influencing factor affecting attitudes toward acceptance or willingness to continue using these information services or new technological systems, and that it plays a crucial role in technology acceptance.

E. AI Usage Satisfaction and Continued Intention to Use AI Have a Positive Correlation

Perceived usefulness significantly influences students' attitudes toward the application of artificial intelligence in education [55]. The research results showed that AI usage satisfaction has a positive correlation with the intention to continue using AI. In other words, when users are more satisfied with the functions of AI technology, they are more willing to continue using the tool. Ye *et al*. [8] also pointed out that AI has been proven to be a useful academic aid. Therefore, when students achieve academic success with the effective help of AI, they are more likely to continue using AI to support their learning. Chen *et al*. [57] also noted that technological advancements in AI for mobile devices have elevated mobile education to new heights. By offering students greater convenience, enabling interactive and personalized learning within shorter timeframes, these innovations deliver a superior learning experience. This is in line with Saadé and Kira's [24] argument that direct use or past experiences with a system can have a positive impact on users' willingness to use it. Additionally, Yuan *et al*. [33] found that the decision to continue using a service is based on satisfaction with the experience.

F. Validation of the Extended AIDUA Model

The cognitive appraisal theory in education focuses on how individuals evaluate and interpret their experiences, influencing their emotional responses and motivation [15]. However, understanding the factors influencing customer willingness is a complex process [5]. Traditional models fail to capture the dynamic interaction between technological features and application environments, limiting their explanatory power when adopting AIGC tools [58]. Therefore, Gursoy *et al*. [5] proposed the AIDUA model, which posits that acceptance generation involves three stages, primary evaluation, secondary evaluation, and outcome

phase, before users decide whether to adopt AI devices. Building upon Gursoy *et al*.'s [5] conceptual framework, this study constructed a three-stage acceptance model based on six variables, and innovatively expanded the AIDUA framework by introducing an AI hallucinations variable. The proposed path hypotheses revealed that personification and hallucinations play significant predictive roles in primary evaluation. Furthermore, the validation of the proposed hypothetical model aligns with Bai and Yang's [58] perspective that, within the AIGC context, technology acceptance behavior is influenced by multiple factors. These factors not only affect technological preference and adoption intent, but also alter the strength of key drivers within the acceptance pathway.

VI. Conclusion and Recommendations

A. Conclusion

Use of AI tools by users in various contexts, including the field of education, has not yet been widely confirmed. Exploring how AI acceptance can contribute to the widespread adoption of AI is a key focus. Based on the AIDUA model, this study examined the relationships between AI anthropomorphism, AI hallucinations, trust in AI, usage anxiety, usage satisfaction, and the intention to continue using AI in the context of AI-assisted learning among Chinese vocational college students. The research results showed the following: 1) AI anthropomorphism was positively correlated with AI hallucinations and trust in AI, but was negatively correlated with AI usage anxiety; 2) AI hallucinations had a positive correlation with AI usage anxiety but a negative correlation with trust in AI; 3) AI usage anxiety had a negative correlation with trust in AI, with AI usage satisfaction, and with the intention to continue using AI; 4) Trust in AI had a positive correlation with AI usage satisfaction and with the intention to continue using AI; 5) AI usage satisfaction had a positive correlation with the intention to continue using AI.

Based on the results, the AIDUA model effectively explains user satisfaction and continued intention to use AI. From a theoretical perspective, the study highlights the impact of AI hallucinations, as users are more likely to experience usage anxiety and to lose trust in the technology when faced with serious errors in responses.

B. Implications

Due to AI technology, the digital transformation of education has been rapid, meaning that effective human-machine collaboration is essential in this age of "AI + Education". The results of this study offer important insights for researchers and administrators, as they clarify the factors which influence users' willingness to accept AI. The main theoretical contribution of this study is the extension of the AIDUA model by formally introducing AI hallucinations as a cognitive risk construct that mediates users' affective evaluations. By accounting for this important, emergent technological phenomenon, this integration enhances the explanatory power of the model. Specifically, by positioning AI hallucinations as a key antecedent in the primary appraisal stage, this research shows how they shape subsequent anxiety and trust, thus providing a more nuanced framework which helps to better understand the dynamics of acceptance. Future researchers can refer to this enhanced model as a flexible theoretical basis on which to explore AI acceptance in a variety of contexts.

Moreover, the research results revealed that when AI is anthropomorphized, it may more easily gain users' recognition, which is a key factor in increasing user satisfaction and promoting long-term reliance on and loyalty to AI. Therefore, engineers and designers should focus more on user experience and meeting user needs when designing and improving AI products. Additionally, the anthropomorphism of AI is seen by people as interacting with a human-like entity. This interaction transcends a mere user experience; it becomes a social experience that merges the virtual and real worlds. Artificial Intelligence in Education (AIED) is not only an empirical science but also a design science. As a design science, it should employ human-centered design methodologies, empowering stakeholders with genuine agency in shaping digital tools. Therefore, in the research, development, and design of artificial intelligence, it is important to consider not only the direct relationship between students and technology, but also how this technology mediates relationships, that is, student-technology (partner)-teacher and student-technology (environment).

It is crucial to emphasize that the primary goal of AI technology is to enhance learning efficiency rather than to diminish critical thinking. When used appropriately, AI can actually bolster users' critical thinking skills. Therefore, attention should be paid to how students use AI, their usage patterns, and their motivations to ensure effective use. More importantly, cultivating students' digital literacy and AI literacy is essential, enabling them to master digital learning strategies.

C. Research Limitations and Future Recommendations

Although this study provides novel insights by validating the AIDUA model in the context of AI-assisted learning, several limitations should be noted. First, the use of a convenience sampling method, while pragmatically justified for efficiently collecting data from the specific target population of Chinese vocational students with AI experience, may constrain the generalizability of the findings. Although the sample covers a wide range of institutions, its concentration in liberal arts and engineering majors, coupled with the underrepresentation of other disciplines such as education, language and literature, and nursing (with a total sample size of less than 45 in these fields), may lead to a representational bias. Second, as a cross-sectional study, it only captured participants' attitudes at a single point in time.

Furthermore, while the model demonstrates strong explanatory power, many aspects of this emerging field remain unexplored. To address these limitations and further evaluate the explanatory power of this extended AIDUA model, three specific research directions are recommended for future inquiry. First, cross-cultural replication studies are needed to verify whether the influence of AI hallucinations on acceptance holds across different educational systems and cultural backgrounds. Second, longitudinal research designs would be invaluable to trace the causal relationships and evolution of key constructs such as trust and anxiety over

time. Third, employing mixed-methods approaches that integrate quantitative surveys with qualitative interviews could yield deeper, nuanced insights into the underlying mechanisms and contextual factors driving students' engagement with AI-assisted learning.

AI holds a unique position in education, functioning as a tool, a partner, or even a virtual teacher. Despite recognition of its potential, the adoption of AI technology is still in progress. The effectiveness of using AI and choosing among its various functionalities remains opaque for many. Ongoing empirical research and the development of relevant theoretical models are essential for facilitating AI's widespread integration into educational practices.

Looking ahead, human-machine collaboration will likely become ubiquitous for those with internet access, much like the use of search engines or apps for daily tasks. However, in regions with underdeveloped internet infrastructure, there is a risk that the digital divide may deepen. Therefore, addressing and mitigating this divide to promote digital equity is a pressing challenge that requires immediate attention.

Ethics Statement

The study was approved by the Academic Ethics Committee of Hainan Vocational University of Science and Technology (HKD-2022-36).

Informed Consent for Participation

All participants provided an informed consent statement.

Artificial Intelligence Usage Scope Statement

In this study, Generative artificial intelligence (DeepL, DeepSeek-V3.1 and Kimi V1) was used to review grammar and spelling during the writing process to enhance the readability and linguistic quality of the manuscript.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

J.-H.Y.: Conceptualization, Data Curation, Formal analysis, Investigation, Methodology, Project administration, Validation, Writing—Original Draft; X.Y.: Conceptualization, Data Curation, Formal analysis, Investigation, Methodology, Validation, Writing—Original Draft; B.L.: Methodology, Writing—Original Draft, Writing—Review & Editing; W.N.: Data Curation, Validation, Writing—Review & Editing; J.-C.H.: Supervision, Writing—Review & Editing; L.W.: Writing—Review & Editing. All authors have read and agreed to the published version of the manuscript.

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Appendix: Questionnaire

No.		Items	M	SD	FL
1	AI Anthropomorphism	When I interact with AI, I feel like it is intentional.	3.77	0.83	0.75
2		When I interact with AI, I feel it has emotions.	3.88	0.83	0.68
3		When I interact with AI, I feel it has free will.	3.66	0.82	0.69
4		When I interact with AI, I feel it has its own emotions.	3.58	0.88	0.78
5		When I interact with AI, I feel like it is conscious.	3.99	0.86	0.80
1	AI Hallucinations	AI generates answers based on false information.	3.38	1.14	0.74
2		AI may provide incorrect answers.	3.17	1.17	0.78
3		AI sometimes provides inconsistent answers to questions.	3.37	1.18	0.81
4		AI may produce contradictory answers.	3.34	1.16	0.80
5		AI may exhibit errors in copying text.	3.16	1.17	0.74
6		AI may produce nonsensical output.	3.21	1.21	0.83
1	AI Use Anxiety	When I use AI, I worry it might deceive me.	3.22	1.21	0.80
2		I easily feel anxious when using AI technology.	3.09	1.29	0.83
3		AI may influence my thought processes.	3.13	1.30	0.79
4		AI may interfere with my freedom of expression.	3.17	1.24	0.82
1	AI Trust	I believe AI is trustworthy.	3.70	1.00	0.76
2		I believe the AI's responses is optimal.	3.69	1.02	0.76
3		I believe the answers provided by AI are correct.	3.81	1.00	0.73
4		I believe AI can guarantee user anonymity.	3.56	1.02	0.72
5		I believe AI will not leak my personal information.	3.61	1.03	0.72
1	AI Use Satisfaction	AI helps me learn knowledge faster.	3.85	1.02	0.85
2		AI helps me acquire the relevant knowledge I need.	3.67	1.03	0.86
3		The AI's responses can be applied to my academic studies.	3.77	1.00	0.85
4		AI is well-suited as a tool for reviewing knowledge.	3.72	1.03	0.85
5		The feedback provided by AI helps increase my understanding of knowledge.	3.84	1.04	0.84
6		AI is an excellent learning companion.	3.68	1.01	0.86
1	Continued Intention to Use AI	I would consider using different versions of AI in the future.	3.64	1.09	0.79
2		I want to continue using AI to help me learn.	3.76	1.07	0.78
3		I would recommend AI to others.	3.85	1.08	0.76
4		If similar AI software becomes available in the future, I would also consider trying it.	3.91	1.05	0.77
5		In short, I will continue using AI in the future.	3.88	1.06	0.79

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