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AIDUA in Action: Exploring Group Differences in ChatGPT Acceptance in Higher Education via Multi-Group Analysis.

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Abstract:
The rapid development of Generative AI (GAI) Chatbots presents new educational opportunities and challenges. While previous studies have examined Chatbot acceptance among students using traditional frameworks such as the Technology Acceptance Model (TAMs) and the Unified Theory of Acceptance and Use of Technology (UTAUT), these models cannot capture the intelligent attributes of AI technology. This study examined students' acceptance of chatbots using the Artificial Intelligence Device Usage Acceptance (AIDUA) model to explore usage group differences among higher education students. The multi-group analysis (MGA) findings address no significant moderation effect by the ChatGPT functions between the constructs, but a substantial influence by the academic field (STEM vs. non-STEM students). The results showed different effect sizes in the relationships of (Hedonic motivation, Performance Expectancy), (Performance expectancy, Emotion), and (Emotion, Willingness to accept ChatGPT). Based on the results, AI companies are advised to tailor content to educational fields and needs and refine their tools to enhance student experiences.

Keywords
AI Chatbot, AIDUA, Technology Acceptance, Higher Education, Multi-group Analysis.

1. Introduction:

Noticeably, world hustles have increased regarding the empowered capabilities of AI-generated content (AIGC), which has become a critical player internationally, serving the live needs of societies by automating tasks, dealing with vast amounts of information, and providing continuous assistance. In 2023, numerous international technology organizations enhanced and replicated specific AI-generated content tools. Presently, an increased number of businesses are emerging with AI-generated content products. For instance, Microsoft has invented "Bing" to advance the outcomes and quality of search. OpenAI technical tools have fascinated universal minds and occupied a significant vigor in computing techniques, especially while talking about the invention of the Chat Generative Pre-Trained Transformer "ChatGPT" (https://openai.com/index/chatgpt/), which is one of the fascinating frontier AI Chatbots that can generate content (e.g., images, text, and videos) with a customized style (Raffel et al., 2020). ChatGPT can accomplish nearly all kinds of data-checking orders impressively and provide valuable outcomes in some domains requiring expert experience in medical, judicial, and financial fields, for example, passing the American Medical Examination (Kung et al., 2023). Historically, ChatGPT was primarily processed by GPT-3.5, then the new GPT-4 version was introduced to the market. In 2023, with the announcement of GPT-4 developed by OpenAI (OpenAI, 2023), ChatGPT got a powerful update with advanced functions; for example, users can now insert texts and pictures semantically. Lately, the OpenAI company has revealed the latest versions of ChatGPT (GPT-4o) (OpenAI, n.d.-a) and (O1) (OpenAI, n.d.-b). The most instinctive feeling of using ChatGPT is that it can precisely recognize the user's intention and generate numerous types of texts in the interactive process of conversation (T. Wu et al., 2023). ChatGPT functionalities have been studied in many areas by indicating its potential and challenges in healthcare (Cascella et al., 2023), insurance (Ressel et al., 2024), and education (Lo, 2023). Initially, Chatbots in higher education were found to be an effective tool for refining student engagement and satisfaction (Firat, 2023). ChatGPT is helpful for education (Dwivedi et al., 2023). Students admire the abilities of ChatGPT and find it interesting, motivating, and useful for their studies and work (Shoufan, 2023). Despite ChatGPT's abilities, it still has certain limitations, such as ethical considerations, risks of misuse and inadequate or unethical deployment, loss of integrity, and many more (Kasneci et al., 2023). ChatGPT is a potential threat to the integrity of online exams, particularly in tertiary education settings where such exams are becoming more prevalent (Susnjak & McIntosh, 2024). OpenAI (OpenAI, 2023) advises educators that "ChatGPT" may produce content that perpetuates harmful biases and stereotypes. Furthermore, ChatGPT is often difficult to understand or predict because of its user interactions. This might discourage many students from using it if they seek a rapid solution to a problem.

ChatGPT marks an essential advancement in generating texts, photos, and ideas, offering students valuable academic support. However, research on student acceptance of AI chatbots remains limited (Hwang & Chang, 2023). A previous study highlighted the need to explore academics' opinions and attitudes toward ChatGPT and how to enhance customer-AI bot interaction frameworks and the requirement of more empirical studies to develop theories like the AIDUA model (Gursoy et al., 2019). This article aims to explore students' standpoints utilizing the AIDUA model and provide a deeper understanding of group differences in Chatbot usage and its impact on e-learning. Moreover, Initial findings highlight interactive communication as its most popular function (Ma & Huo, 2023), leaving an open question regarding the potential moderating effects of ChatGPT's different functions and different academic fields on students' behavioral intentions toward ChatGPT usage.

The ground-breaking aspects of this article are as follows: First, this study reviews Chatbot adapting actions by studying equal willingness and rejections to use ChatGPT, continuing to verify the AIDUA model in the educational domain. Second, it explores the moderating effects of ChatGPT's most frequently used functions and the differences between STEM (Science, Technology, Engineering, Mathematics, etc.) and non-STEM (Arts, Social Sciences, Humanities, etc.) groups of students in the relationships of the model constructs. The findings will assist technology organizations in enhancing their strategies for facilitating the use of GAI Chatbot tools and contribute to the existing literature on AI in e-learning and higher education.

The next segments of this paper are designed as follows. The upcoming headline discloses the theoretical background, literature review, hypotheses development, and the methodology used in this research. In conclusion, discussing the crucial discoveries was handled, closing with limitations and likely future research gaps.

2. Theoretical background:

2.1 AI device use acceptance framework (AIDUA):

The AIDUA (Gursoy et al., 2019)proposes a three-stage process for customers' intention to use AI. In the primary appraisal phase, factors such as social influence, hedonic motivation, and anthropomorphism shape initial perceptions. The secondary appraisal phase involves users' assessments of performance expectancy, effort expectancy, and emotions. Finally, the outcome stage determines whether customers accept or reject AI tools. The importance of the AIDUA model is that, rather than relying on classic models (e.g., TAM and UTAUT) that define acceptance as the absence of refusal (Chi et al., 2023), it indicates that acceptance and rejection may co-exist. The AIDUA theory has so far been tested in artificially intelligent robotic devices in Chatbots (Ma & Huo, 2023), tourism (Chi et al., 2022), and more. Furthermore, no reviews have used this framework in the educational context. The research aims to determine if this model can be improved to enhance Chatbot acceptance and usage in higher education.

2.2 Task-Technology Fit Model (TTF)

The TTF model (Goodhue & Thompson, 1995) suggests that the effectiveness of technology depends on how well its capabilities align with the requirements of a given task. According to TTF, information technology will only be utilized if its features adequately support the user's activities. Users are likely to select tools and methods that provide the highest net benefit for task completion, while technologies that fail to offer sufficient advantages are unlikely to be adopted. Consequently, students are expected to use ChatGPT for their learning if the tool successfully fulfills the task given through its features. Earlier research studies highlighted that combining the TAM, ECT, and TTF models is valuable for gaining insights into software utilization across diverse scenarios (Dishaw & Strong, 1999, Dhiman & Jamwal, 2023). In the context of e-learning, a recent study explored the crucial role of service associates from Chatbots in mediating student satisfaction, helping them make informed decisions about relying on and acquiring online education (Butt et al., 2021).

Based on the above theories, the author proposed the following research questions:
RQ1. What factors determine students' behavioral intentions toward the usage of ChatGPT for educational purposes?
RQ2. Do different types of ChatGPT features used by students (e.g., writing assistance, research assistance...) moderate the structural relationships influencing their acceptance or objection to using AI chatbots in higher education?
RQ3. Does students' academic background (STEM vs. Non-STEM) moderate the structural relationships influencing their acceptance or objection to using AI chatbots in higher education?

3. Literature review and Hypotheses development:

3.1. Social Influence

Social Influence (SLI) is the degree to which a person perceives that crucial others think she/he should use a specific technology (Venkatesh et al., 2003), which refers to the influence of such (friends, family, etc.) on a person's behavior regarding technology use. Social Impact Theory proposes that users are more likely to follow group norms if it is important to them (Latané & Wolf, 1981). They might gain more insights about the technology from influential individuals, which helps to lower their sense of uncertainty (Cheng et al., 2022). It is found that SLI is one of the primary factors that positively influence the acceptance of AI in education (Prasad et al., 2018). SLI will lead users to accept Chatbots since it deeply affects users' evaluations of effort expectancy and performance expectancy (Chi et al., 2022). Consequently, the upcoming hypotheses have been created:
H1a. Social influence positively impacts students' performance expectations with ChatGPT.
H1b. Social Influence Negatively Impacts Students' Effort Expectancy of ChatGPT.

3.2. Hedonic Motivation

Hedonic Motivation (HDM) is the playfulness or entertainment of using technology (Venkatesh et al., 2003); it is the enjoyment, pleasure, or fun a person experiences when using technology or engaging in an activity. It plays a vital role in accepting and using technology (Brown & Venkatesh, 2005). It is also defined as a user's subjective experience, such as the satisfaction and enjoyment of adapting modern technologies (Vitezić & Perić, 2021). An earlier study has shown that enjoyable technologies improve customers' intention to meet with satisfaction and acceptance of using a specific technology (Ashfaq et al., 2020). A positive chat will help customers understand ChatGPT's flexibility and dynamics, which assist them in completing tasks. Moreover, the initial studies have found a direct influence of HDM as a predictor of the expected performance and effort associated with Chatbot (Bhuiyan et al., 2024, Mei et al., 2024). Therefore, if students perceive ChatGPT for learning purposes as enhancing their fun and enjoyment, they are likely to have a positive evaluation of the tool. However, students' hedonic motivation and adoption of AI platforms have received limited attention in the existing studies (Qu & Wu, 2024). Correspondingly, the following hypotheses have been established:

H2a. Hedonic motivation positively influences the students' performance expectancy while using ChatGPT.

H2b. Hedonic motivation negatively influences the students' effort expectancy while using ChatGPT.

3.3. Perceived Humanness

Perceived Humanness (PH) refers to the degree to which a person considers that a conversational agent (such as a Chatbot) might be human (Schuetzler et al., 2020). This is the extent to which an individual believes that a Chatbot exhibits responses that are typically associated with humans. Humanness is a crucial concept for studying human–chatbot interaction (Rapp et al., 2021). In AI Chatbot research, user emotions are significantly impacted by their ability to understand humanness and provide human-like responses. A MANOVA indicated that users chatted with the Chatbot longer than humans (Hill et al., 2015). Users perceived a Chatbot with high-level conversational skills to be more engaging and human-like (Schuetzler et al., 2020). Moreover, an initial study found that the social presence of an educational robot influences the user's performance and effort expectations (Guggemos et al., 2020). In the AIDUA model, PH was mentioned as "anthropomorphism," which refers to the degree to which an object (computer-animal products) possesses human-like traits such as physical appearance, self-awareness, and emotional capacity (Kim & McGill, 2018). ChatGPT is a text-based Chatbot with no anthropomorphic appearance, and it has already been proposed that PH is more appropriate than anthropomorphism as an antecedent (Ma & Huo, 2023b). Similarly, ChatGPT's talks are infused with humanness, which enables users to assess their efforts when interacting with ChatGPT and raises their expectations for performance. Consequently, the following theories have emerged:

H3a. Perceived humanness will positively affect the students' performance expectations for ChatGPT.

H3b. Perceived humanness will negatively influence the students' expectation of effort in ChatGPT.

3.4. Influence of Performance Expectancy on Emotion

Performance expectancy (PPE) refers to the users' belief that utilizing ChatGPT will assist them in completing a specific task (Venkatesh et al., 2003). It reflects the perceived usefulness and efficiency of the technology in improving task performance. Higher PPE typically leads to

greater intention to use the system, as users expect it to deliver tangible benefits. In education, ChatGPT can assist students with assignment writing, research assistance, exam preparation, interactive learning support, and many other facilities. In the AIDUA, PPE played a crucial role in influencing the user's emotions (Gursoy et al., 2019; Li et al., 2024). Thus, if students' expectations regarding ChatGPT performance are fulfilled, they are expected to be emotionally connected with the usage of the technology. Consequently, the following hypnosis has been issued:
H4. The perceived performance expectancy of ChatGPT will positively impact Students' emotions.

3.5. Influence of Effort Expectancy on Emotion

Effort Expectancy (PEE) is the ease of use aligned with adopting the ChatGPT (Kim & McGill, 2018). This concept pertains to users' insights into the ease of dealing with and using ChatGPT for multiple responsibilities and how clear and understandable the conversations are. Users' views on effort expectancy significantly influence their aim to adapt and use an innovative technology. In education, this refers to how easily students perceive ChatGPT for learning tasks, such as understanding course material or completing assignments. If students are using ChatGPT intuitively and its outputs are easy to comprehend, they are more likely to adopt it. For example, a student might use ChatGPT to quickly generate essay ideas because it provides clear and easily understandable suggestions with minimal effort. The positive relationship view was backed by the UTAUT (Kim & McGill, 2018) and the TAM (Fred D. Davis, 1989), opposite to the AIDUA, which considers the PEE as the perceived difficulty and the complexity of using AI devices, which is going to have a negative relationship with the user's emotions (Chi et al., 2023). However, in this study, we define PEE as per the AIDUA point of view. Therefore, the upcoming hypothesis has formed:
H5. The perceived effect expectancy of ChatGPT will negatively influence students' emotions.

3.6. Emotion

Emotion has been defined as subjective mental states that affect an individual's selection of emotional information (Schoefer & Diamantopoulos, 2008). According to the Cognitive theory (Lazarus, 1991) posits that during a complex evaluative process, emotions towards a device will emerge and consequently influence user willingness to acceptance the use of service or objection to use it. Positive emotions, including relaxation, contentment, hopefulness, satisfaction, and pleasure, have been shown to affect consumption-related behaviours (Watson & Spence, 2007), and then it will lead to more willingness to accept to use the device. On the other hand, unpleasant feelings like boredom, sadness, hopelessness, dissatisfaction, and annoyance will lead to objections to using the device (Gursoy et al., 2019). Thus, students are expected to make their decision regarding ChatGPT usage based on their emotions while dealing with it for educational purposes. Therefore, the upcoming hypotheses have formed:
H6a. The student's emotions will negatively influence students' willingness to accept the use of ChatGPT.
H6b. The student's emotions will negatively influence students' objections to using ChatGPT.

According to the TTF theory (Goodhue & Thompson, 1995), Users will select tools and methods that provide the highest net benefit for task completion. A recent study examined the moderation role of chatbot conversation types (task-related) over process fluency and found that it enhances customer satisfaction and usage intention (Shams & Kim, 2024). Earlier studies have examined the role of personal innovativeness (An individual's willingness to adopt new

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technology) over the behavioral and usage intention relation, and it was found to moderate the relation. (Strzelecki et al., 2024,Q. Wu et al., 2025). Students' evaluation of and engagement with AI chatbots such as ChatGPT are likely influenced by how well the technology supports their discipline-specific learning tasks. Since STEM and non-STEM students engage in fundamentally different academic activities. Thus, the following general hypotheses are proposed:

H7. ChatGPT's function moderates the relationships between model constructs, such that the effects vary based on the function used.

H8. The structural relationships between the model constructs differ significantly between STEM and non-STEM student groups.

The following **Fig.1** represents the proposed model of the study:

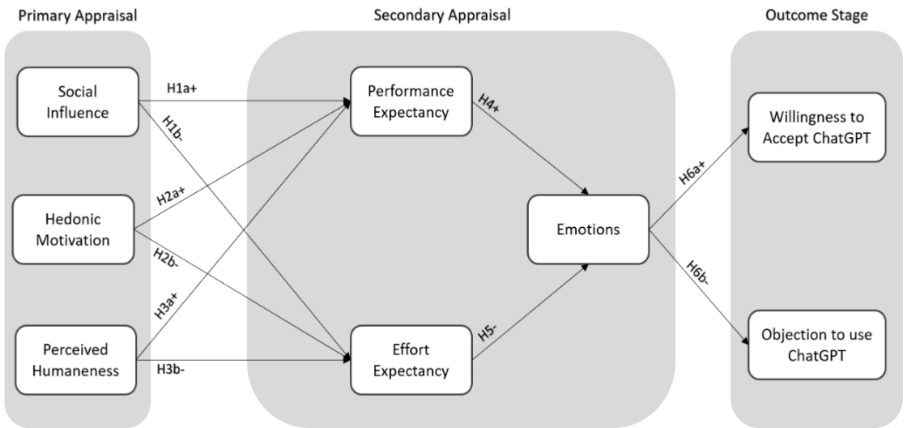

Fig. 1. Proposed model.

4. Methodology:

The researcher used the Confirmatory Factor Analysis (CFA) to evaluate the measurement model, followed by the Structural Equation Modeling (SEM) to check causal links between the proposed model's constructs. Data was collected over an online survey regarding demographic information and ChatGPT insights. The author used the purposive sampling method to collect the data from selected universities based on the top-ranked and low-ranked universities in the south of India. The author got 399 completed responses were analyzed with the help of SPSS 27.0 and Amos 25.0 software.

4.1. Questionnaire design

The survey structure was designed to gather students' demographic information and their perceived opinions about the constructs of ChatGPT. The questionnaire items were adapted from established constructs Table 1. Six items for SLI, five items for HDM, four items for PPE, four items for PEE, five items for EMS, three items for WA, and four items for OA have been adapted from Ref. (Gursoy et al., 2019). Four items for PH have been adapted from Ref. (Ma & Huo, 2023). The primary scale entailed 35 items overall and was slightly modified to fit the context. Items were measured by the Likert-type scale (five points) labeled 1 for "Strongly Disagree" and 5 for "Strongly Agree".

4.2. Population, Sampling, and Data Collection

The study population is students of Indian universities who are using ChatGPT. The university's selection criteria depended on the top and low-ranked universities among the population (National Institutional Ranking Framework: https://www.nirfindia.org/), mixing private and public universities. The author used the "Google Forms" platform (https://www.google.com/forms/about/) to establish the questionnaire. Then share it via online channels (e.g., Emails, WhatsApp, and Facebook) with the assistance of the university's instructors. The purposive sampling methods were used to choose the targeted sample size. The "sample-to-item ratio" strategy was implemented to draw a particular sample size from the population. It implies that for each item in the questionnaire, 10-to-1 respondents are sufficient to avoid sampling bias (Memon et al., 2020). This survey has 35 items, so 350 samples are enough. To decrease the sample bias, a greater sample size of 429 responses was gathered. Only 399 questionnaires were valid for analysis, with a response percentage of 93%. The criteria for identifying invalid samples involved removing incomplete responses, as 30 respondents failed to answer certain questions in their online responses for various reasons.

From April 16th to May 15th, 2025, the author distributed online questionnaires. To fit with the research design of the article, the author selected the most frequently used functions of ChatGPT in the context of e-learning (writing assignments, research assistance, exam preparation, and interactive learning support) and kept the opportunity to mention any other functions they might use. To avoid confusion about the multiple versions of ChatGPT, the author has selected one version of ChatGPT, GPT-3.5 (free version), which is accessible to any user. The author used two filter questions before starting the survey: "Did you have any conversation with ChatGPT before?" and "Are you a higher educational student?" to eliminate the invalid questionnaire, which does not meet the sample requirement.

4.3 Data description

The overall completed questionnaire collected was 399, and found that the survey was spread among 59.4% of males, 40.1% of females, and 0.5% belonging to the other gender groups. Over 80% of the students are aged between 18 and 25 years old, and 52.1% hold a senior high school degree. The most common ChatGPT functions used are research assistance, writing assignments, and exam preparation. The responders didn’t highlight any other used functions of ChatGPT. Finally, the majority of them belong to non-STEM fields. The overall demographic characteristics are presented in **Table 1.**

Table 1. Demographic characteristics (N = 399).

Measure	Items	Frequency	Percent
Gender	Male	237	59.4%
	Female	160	40.1%
	Other	2	0.5%
Age	18-25	322	80.7%
	26-35	70	17.5%
	36-45	7	1.8%
What’s the highest level of education you completed?	Senior high school	208	52.1%
	Bachelor’s degree	112	28.1%
	Master’s degree	71	17.8%
	Doctor’s degree	8	2.0%

What is your academic field of study?	STEM (Science, Technology, Engineering, Mathematics, etc.) Non-STEM (Arts, Social Sciences, Humanities, etc.)	191 208	47.9% 52.1%
ChatGPT's function you use most for study	Writing Assignment Research Assistance Exam Preparation Interactive learning support	108 112 72 107	27.1% 28.1% 18.0 % 26.8 %

5. Results:

5.1. CFA

A Confirmatory factor analysis was conducted to evaluate the measurement model. The following model fit indices have been evaluated based on the threshold values in Ref. (Dash & Paul, 2021). $\chi 2/DF = 1.604$, RMSEA = 0.039, CFI = 0.975, IFI = 0.975, and TLI = 0.972 designate the model validity to represent the data (**Fig. 2**). The convergent validity (CV) results are demonstrated in **Table 2**, where the values were normally distributed. The internal consistency was measured by Cronbach's alpha values (> 0.7) for all constructs (Nunnally, 1978). The composite reliability (CR) for the constructs has become (> 0.7) (Hair et al., 2012), the average variance extracted (AVE) for each construct is (>0.5), and MSV values are less than AVE (Bagozzi, 1980). Finally, the Items (SLI5 and HDM4) have been removed due to lower loading values (<0.4).

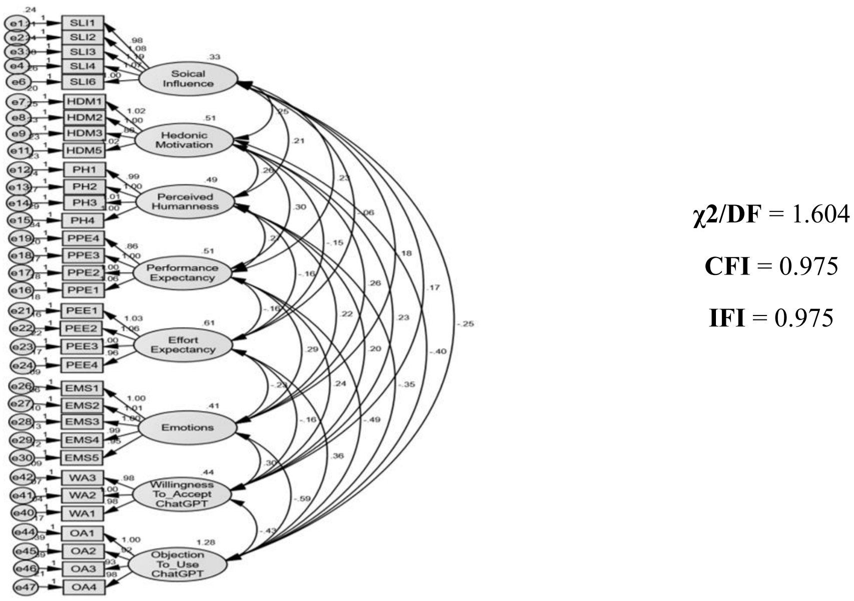

Fig. 2. CFA results.

Table. 2. Reliability and Validity results.

Constructs	Item	M	SD	Loadings	α	CR	AVE	MSV
Willingness to Accept ChatGPT	WA1	3.85	0.683	0.951	0.950	0.950	0.863	0.506
	WA2	3.80	0.716	0.930				
	WA3	3.78	0.718	0.906				
Social Influence	SLI1	3.69	0.749	0.755	0.875	0.877	0.588	0.376

	SLI2	3.71	0.769	0.807				
	SLI3	3.61	0.846	0.812				
	SLI4	3.53	0.870	0.709				
	SLI6	3.68	0.770	0.746				
Hedonic Motivation	HDM1	3.56	0.857	0.851	0.884	0.884	0.658	0.376
	HDM2	3.58	0.872	0.821				
	HDM3	3.54	0.843	0.729				
	HDM5	3.54	0.873	0.837				
Perceived Humanness	PH1	3.51	0.844	0.876	0.884	0.885	0.657	0.292
	PH2	3.50	0.856	0.819				
	PH3	3.44	0.880	0.808				
	PH4	3.41	0.889	0.793				
Perceived Performance Expectancy	PPE1	3.34	0.871	0.876	0.897	0.899	0.690	0.397
	PPE2	3.35	0.828	0.867				
	PPE3	3.37	0.847	0.847				
	PPE4	3.35	0.851	0.724				
Perceived Effort Expectancy	PEE1	2.60	1.207	0.877	0.941	0.933	0.776	0.221
	PEE2	2.69	1.220	0.858				
	PEE3	2.66	1.220	0.902				
	PEE4	2.66	1.196	0.886				
Emotion	EMS1	3.68	0.703	0.907	0.950	0.953	0.801	0.663
	EMS2	3.66	0.697	0.931				
	EMS3	3.61	0.717	0.899				
	EMS4	3.60	0.732	0.871				
	EMS5	3.68	0.699	0.864				
Objection to Use ChatGPT	OA1	3.02	0.884	0.938	0.934	0.942	0.801	0.663
	OA2	3.01	0.892	0.857				
	OA3	3.02	0.877	0.859				
	OA4	3.01	0.819	0.924				

Note: M = Mean, α = Cronbach's alpha, S.D. = Standard Deviation; CR = Composite Reliability; AVE = Average Variance Extracted; MSV = Maximum Shared Squared Variance. D = Deleted item, *** $p < 0.001$.

Table 3. Showing values range from 0.767 for SLI to 0.929 for WA, all are above the acceptable threshold of 0.5, suggesting satisfactory convergent validity. Among the observed correlations, the highest is between WA and itself. EMO and OA exhibit a strong negative correlation implying that students who perceive higher positive emotion are less likely to have objection over useing the ChatGPT in their studies. EMO is positively correlated with WA, indicating that students who perceive higher emotions are more likely to have willingness over ChatGPT usage. PPE shows moderate correlations with EMO and OA, suggesting that the perceived performance of ChatGPT's jointly influence student's emotions regarding ChatGPT usage and motivate them to use it.

Table 3. Construct correlations.

	WA	SLI	HDM	PH	PPE	PEE	EMO	OA
WA	**0.929**							

SLI	0.448	**0.767**						
HDM	0.486	0.613	**0.811**					
PH	0.423	0.534	0.515	**0.811**				
PPE	0.497	0.568	0.590	0.540	**0.831**			
PEE	-0.312	-0.126	-0.265	-0.294	-0.287	**0.881**		
EMO	0.711	0.503	0.567	0.499	0.630	-0.470	**0.895**	
OA	-0.569	-0.392	-0.490	-0.442	-0.605	0.409	-0.814	**0.895**

5.2. Structural Model and Hypotheses Evaluation

The researcher has built an SEM via AMOS 25.0 to evaluate the proposed model. The **Fig. 3** displays the SEM indices. **Table 4** illustrates all hypotheses along with their relational paths and path coefficients (β) and provides the hypotheses' results. All hypotheses were supported despite the H1b, which indicates an insignificant relation between SLI and PEE.

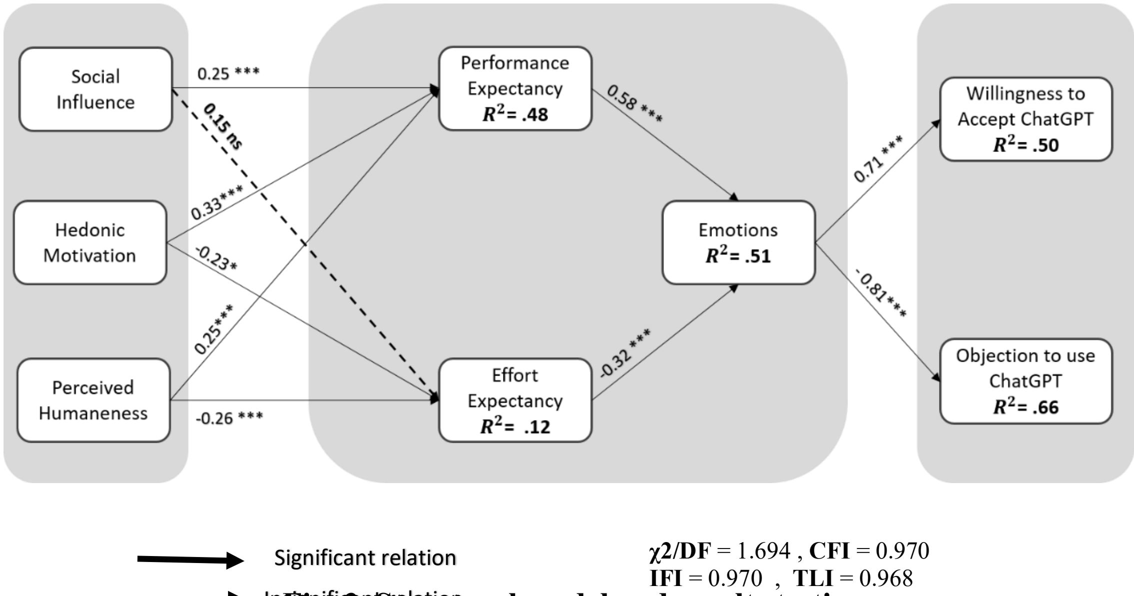

Fig. 3. Structural model and results testing.

Table 4. Hypotheses test.

Hypotheses	**Relations**	**(β)**	**P**	**Result**
H1a	SLI→ PPE	.25	***	Supported
H1b	**SLI→ PEE**	**.15**	**.055**	**Rejected**
H2a	HDM→ PPE	.33	***	Supported
H2b	HDM→ PEE	-.23	.002	Supported
H3a	PH→ PPE	.25	***	Supported
H3b	PH→ PEE	-.26	***	Supported
H4	PPE→ EMO	.58	***	Supported
H5	PEE→ EMO	-.32	***	Supported
H6a	EMO→ WA	.71	***	Supported
H6b	EMO→ OA	-.81	***	Supported

Note: (β) = Path coefficient, *P < 0.05, **P < 0.01, ***P < 0.001.

5.3. Multi-group analysis (MGA)

An MGA has been conducted to explore any potential moderating effect of the most frequently used functions of ChatGPT between students (writing assignments, research assistance, exam preparation, and interactive learning support) and ChatGPT versions (GPT-3.5, GPT-4) between the entire model constructs. To proceed with this study, a minimum of 100 elements is required for each major group or subgroup in the sample (Sudman, 1976). As the data collected in **Table 1**, there were only 72 samples over the Exam Preparation feature. Hence, the author combined these samples with the interactive learning support samples to make it easier to calculate and proceed with the analysis. The analysis involved comparing the unconstrained and constrained models (Savalei & Kolenikov, 2008). To assess the moderating effects of the most frequently used ChatGPT function and ChatGPT version on the relationships between the model variables, the unconstrained models for the groups representing the moderating variables were compared with their respective measurement weight and structural weight models. If moderating effects are present, they will result in statistically significant differences in the empirical relationships between the same model variables (Bamberg, 2003). The author used the chi-square difference ($\Delta\chi2$) test to check the differences through the models (Bryant & Satorra, 2012). If the $\Delta\chi2$ value among the models is statistically significant ($P < 0.05$), it indicates a difference among the groups. Firstly, **Table 5** shows that all of the measurement weight model showed insignificant differences from their unconstrained model for the first moderating variable. This means students across the different groups interpret the constructs similarly. Continuously, the structural weight model was not significantly different, meaning the relationships between the constructs are consistent across the groups based on the different functions. Thus, H7 is rejected. Secondly, the Measurement weight model showed insignificant differences from their unconstrained model for the second moderating variable, meaning students' from different academic discipline understands of the model constructs similarly, but the structural weight model was showing a significantly different, meaning the relationships between the constructs are differ across the groups based on the different academic fields. Thus, H7 is accepted.

Table 5 - Results of comparison among the models

Moderating variables	Model	χ2	Df	Δχ2	Δdf	P Value	Result
ChatGPT's function	Unconstrained	2120.376	1446	---	---	---	---
	Measurement weight	2172.018	1496	51.642	50	0.409	NS.
	Structural weight	2194.302	1516	22.284	20	0.325	NS.
Academic Field	Unconstrained	1434.982	964	---	---	---	---
	Measurement weight	1455.139	989	20.517	25	0.7385	NS
	Structural weight	**1479.749**	**999**	**24.610**	**10**	**0.0061**	**S**

Note: $\chi2$= chi-square value, Df= Degree of freedom, $\Delta\chi2$= chi-square difference, Δdf= degree of freedom difference, NS= not significant, S= significant, *P < 0.05, **P < 0.01, ***P < 0.001.

To examine the moderation effect of the academic field among the relationships between the constructs, a chi-square difference test ($\Delta\chi2$) has been calculated between the unconstrained and the constrained model across the construct paths. If ΔCFI is less than or equal to 0.01 and $p < 0.05$, then the two models are significantly different (Steenkamp & Baumgartner, 1998). The following **Table 6** shows three significant differences, firstly, between HDM and PEE, with a ($\Delta\chi^2$= 4.449) and (P-Value = .035 < 0.05), where the path coefficient (β) for the STEM group was = -.056, while for the Non-STEM group was = -.406. Secondly, between PPE and EMO, with a ($\Delta\chi^2$= 4.934) and (P-Value = .026 < 0.05), where the (β) for the STEM group was = .600, while for the Non-STEM group was = .415. Finally, between EMO and WA, with a ($\Delta\chi^2$= 4.217) and (P-Value = .040 < 0.05), where the (β) for the STEM group was = .836, while for the Non-STEM group was = .649.

Table. 6 - Chi-Square Difference Testing

Path	DF	($\Delta\chi^2$)	P-Value	ΔCFI	Significance
SLI→ PPE	1	2.124	.149	0.000	NS
SLI→ PEE	1	.027	.869	0.000	NS
HDM→ PPE	1	2.800	.094	0.000	NS
HDM→ PEE	**1**	**4.449**	**.035***	**0.000**	**S**
PH→ PPE	1	.454	.501	0.000	NS
PH→ PEE	1	.132	.717	0.000	NS
PPE→ EMO	**1**	**4.934**	**.026***	**0.000**	**S**
PEE→ EMO	1	1.567	.211	0.000	NS
EMO→ WA	**1**	**4.217**	**.040***	**0.000**	**S**
EMO→ OA	1	.253	.615	.211	0.000

Note: Df= Degree of freedom, $\Delta\chi^2$= Chi-Square differences, ΔCFI = change in Comparative Fit Index, NS= not significant, S= significant, *P < 0.05, **P < 0.01, ***P < 0.001.

6. Discussion:

This study reveals several significant findings. First, both SLI and HDM were positively correlated with PPE and negatively with PEE. SLI was found to have an insignificant relationship with the effort expectancy. These results support the AIDUA model and align with the results of many earlier research articles (Gursoy et al., 2019; Li et al., 2024). Second, PH was found to better fit in the AI Chatbot context. PH positively correlates with PPE and negatively with PEE, aligning with previous research on chatbots (Ma & Huo, 2023). Furthermore, PPE was found to positively and significantly influence the students' emotions, while PEE was found to affect students' emotions with a significant negative influence. Finally, students' emotions were found to be a strong predictor of their behavioral intention regarding their willingness and objection to using ChatGPT for their learning interest. The last results are similarly aligned with several past studies (Bai & Yang, 2025; Lin et al., 2020; Somu et al., 2024)

The MGA findings demonstrate that the measurement weight models across all constructs showed no significant differences from the unconstrained models. This indicates that students across different groups defined by ChatGPT's most frequently used functions and versions interpret the constructs consistently. Such measurement equivalence is essential for ensuring the reliability and validity of cross-group comparisons (Chen, 2007). These findings suggest that the constructs were well understood by respondents, regardless of the specific function or version of ChatGPT they used, aligning with the principles of strong metric invariance in SEM analyses (Cheung & Rensvold, 2002). Different potential reasons lie behind this result. First, the sample may represent a relatively homogeneous group of students with similar educational needs and expectations. This homogeneity can result in consistent patterns of perception and behavior, minimizing variations based on function categories. Moreover, students may not be fully aware of functional differences or may not differentiate their experiences based on the function categories. Students may focus on the outcomes delivered by ChatGPT as a whole rather than analyze which function contributed the most. Where users are focused on efficiency, perceived utility often overshadows functional nuances (Ameen et al., 2021). This lack of differentiation can lead to consistent perceptions across groups.

The structural weight model revealed differing results for the two moderating variables. For ChatGPT's most frequently used functions, no significant differences were observed between the unconstrained and constrained models. This implies that the relationships between the model constructs are consistent across groups. Students' usage patterns based on function categories do not significantly influence their behavioral intentions. Students are primarily task-focused, using ChatGPT as a tool to complete assignments, solve problems, or facilitate learning. This pragmatic usage reduces the influence of function-specific differences on their overall behavioral intentions (Dwivedi et al., 2019).

However, the structural weight model for the students' academic fields revealed significant differences, highlighting important moderation of the academic discipline over students' behavioral intentions toward ChatGPT. Specifically, the $\Delta\chi^2$ and ΔCFI values pinpointed significant moderation effects on three critical paths. First, between HDM and PEE, the STEM group's path coefficient (β) was = -.056, while for the Non-STEM group it was = -.406. This suggests an insignificant influence of the HDM over the PEE for the STEM students, while indicating a significant negative impact for the non-STEM students. This implies that the hedonic motivation perceived through ChatGPT will reduce the difficulty or the complexity of using it by the non-STEM students, meanwhile, it might not make any meaningful impact on the STEM students. The author refers this to the fact that STEM students are more likely to deal with numbers and quantitative content, which might make it difficult to build humorous conversations with the STEM students, meanwhile it might be easier to handle a friendly and funny atmosphere while chatting with the non-STEM students as per they are more likely to deal with a qualitative content. Second, between PPE and EMO, the (β) for the STEM group was = .600, while for the Non-STEM group it was = .415. This moderation implies that performance expectancy plays a significant role in developing positive emotions for both groups of students, but has a greater effect on the STEM students. This indicates that ChatGPT might provide greater usefulness for STEM students since they are dealing with more complex content (e.g., mathematical problems, Coding, etc.), thus, their positive emotions will be influenced if they perceive a clear solution to their problems. Finally, the relationship between EMO and WA, where the (β) for the STEM group was = .836, while for the Non-STEM group was = .649. This moderation implies that emotions play an important role in influencing the behavioral intention of both groups of students and shaping their decision into willingness to use ChatGPT in their studies, but has a greater effect on the STEM students. This implies that STEM students are more emotionally driven toward adopting ChatGPT when they perceive it to be useful and effective in handling their academic tasks, especially those requiring technical accuracy and analytical thinking. while emotions also influence non-STEM students' willingness to use the tool, the comparatively lower effect size suggests that their behavioral intentions might be shaped more evenly by other factors, such as facilitating conditions, AI-literacy, or trust.

7. Implications:

7.1 Theoretical Implications

The research study delivers considerable theoretical implications by examining the AIDUA model to fit the e-learning context. First, the study revealed that the AIDUA model is well fit by its constructs in the e-learning context. The results of this study could highlight that students perceive ChatGPT as a flexible tool capable of adapting to multiple tasks, regardless of its specific function. This may reflect a shift in the role of task-technology alignment for tools like ChatGPT, where its advanced natural language processing capabilities make it versatile and reduce the emphasis on function-task alignment. Moreover, the structural weight model revealed significant moderation by academic discipline, which contributes new insights to the literature. These findings collectively imply that AI-based educational tools like ChatGPT should not be viewed as one-size-fits-all solutions. Instead, theoretical models of AI acceptance must account for disciplinary differences, where emotional and cognitive pathways influence technology engagement differently.

7.2 Practical Implications

These findings underscore the importance of tailoring AI-based educational chatbot tools not only to functional needs but also to the emotional and cognitive expectations of students from different academic disciplines. Specifically, enhancing performance features (e.g., accuracy, problem-solving ability) may be more impactful for STEM students, while integrating hedonic elements such as friendliness and conversational tone could improve adoption among non-STEM students, who may respond more positively to enjoyable and less technical interactions. For AI companies, students' behavioral intentions were consistent across different ChatGPT function categories, suggesting providing more customized content to align with the educational function. Educational institutions can leverage this versatility by integrating ChatGPT into a broad range of tasks, without the need to customize the tool for specific functions. This reduces the need for extensive training or function-specific adaptations, saving time and resources.

8. Conclusion:

8.1. Summary

This study validated the AIDUA model to fit with students' understanding of their willingness and reluctance to adopt Chatbots for educational purposes. Key findings demonstrated that all of SLI, HDM, and PH positively impact PPE and negatively influence PEE. SLI was found to have an insignificant effect on the PEE. All of PPE and PEE were significantly impacting the students' emotions, which in turn were shaping their willingness and objections to using ChatGPT for their education. There were no significant moderation effects of ChatGPT's functions among the students, but a significant moderation effect of the academic disciplines over the relationships of (HDM, PEE), (PPE, EMO), and (EMO, WA).

8.2 Limitations and Future Research

This study has several limitations. The relatively small sample size limits the generalizability of the findings; future research should employ larger, more diverse samples to provide a more comprehensive understanding of ChatGPT acceptance. While these results offer valuable insights, future studies could extend this research by examining other factors that influence acceptance and rejection in different contexts, such as e-retail, e-shopping, and e-commerce. Moreover, the study included the users of GPT-3.5 only; future studies could include the latest versions of ChatGPT (GPT-4o) and (O1), to investigate the differences in the behavioral intentions regarding the adoption of the ChatGPT tool in different scenarios. Finally, the multi-group analysis has examined the moderation effect of the STEM and non-STEM students, Future studies could further explore the effect sizes between model constructs within each academic discipline to gain deeper insights into AI chatbot acceptance across distinct educational domains.

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