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ChatGPT 在協作學習環境中的應用： AMO 和 TAM 理論的學生互動的實證分析

The Road to Sustainable Digital Education: ChatGPT's Role and Relevance Analyzed through AMO and TAM

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Abstract: As we move towards a more sustainable future, the exploration of integrating Artificial Intelligence (AI) into Collaborative Learning in the educational landscape becomes even more pertinent. Not only does AI offer a means to conserve resources, but it also embodies the promise of delivering optimized learning experiences for students. Harnessing AI to bolster students' learning opportunities and fortify their abilities and motivation within sustainable learning environments is now a research imperative.

This study employed OpenAI developed ChatGPT as an object, and based on the ability, motivation, and opportunity (AMO) theory, an empirical analysis was carried out. AMO theory postulates that an individual's performance is affected conjointly by ability, motivation, and opportunity three factors. Through interviewing students and teachers and data analysis, from students' self-efficacy to students' usage, aims to investigate how the ChatGPT influences learning effectiveness and intention of usage. ChatGPT

can effectively enhance students' abilities, motivation, and learning opportunities.
To enhance students' abilities, ChatGPT provides instant information to help boost students' abilities. In the aspect of increasing students' motivation, ChatGPT, through the feedback of interaction, can stimulate students' learning motivation. Concerning increasing learning opportunities, ChatGPT supplies a flexible learning pattern to create more opportunities for learning for students. Meanwhile, by an acceptable technology Model, ChatGPT will significantly affect students' using attitude and further affect using intention. ChatGPT can significantly reshape students' attitudes toward technology, influencing their long-term adoption intention.
Keywords: ChatGPT 1; AMO 2; TAM 3; Collaborative Learning 4

1. Introduction

Collaborative learning is an interactive pedagogical approach that focuses on knowledge creation through student collaboration. It emphasizes the formation of cooperative teams and problem-solving throughout the learning process [1,2]. However, with the advancement of educational technology. The emergence of technological tools and platforms makes students engage in collaborative learning [3], thus expanding students' learning effectiveness and opportunities.

This study explores optimizing collaborative learning processes through the ChatGPT to improve student learning outcomes. AI technology has been continuously advancing, with the emergence of ChatGPT in late 2022 sparking significant debate and consideration of its benefits and potential shortcomings [4]. ChatGPT is a chat generative pretrained chatbot with a conversational AI interface. It is a machine-learning model with human-like text generation capabilities, whose output is nearly indistinguishable from human writing regarding readability and often superior [5,6].

The role of AI in collaborative learning has become increasingly important. As a collaborative partner, AI can provide timely and modifiable feedback, guide students in problem-solving, enhance learning motivation, and provide customized suggestions to help students improve the quality of their work. Previous studies on ChatGPT have mainly focused on ethical and technical aspects [7,8,9] and educational opportunities and risks [10,11], with less attention to concurrent pedagogical models and usage intentions. Since ChatGPT emerged gradually after 2022, and thus, previous relevant research is lacking. Therefore, this study further explores the usage behavior of

ChatGPT. This study aims to address the following research questions:

Sustainable Integration in Modern Learning: How do the application effects of ChatGPT in collaborative learning contribute to long-term sustainable education goals?

Skills for a Sustainable Future: In the context of preparing students for a sustainable future, how does ChatGPT influence students' skills, motivation, and learning opportunities to address global challenges?

Understanding Sustainable Pedagogy with AMO: Utilizing the AMO theory, how can we evaluate the role of ChatGPT in fostering collaborative learning that aligns with sustainable educational practices? Following the above research questions, this study uses AMO theory to propose a new framework for evaluating and understanding the role of ChatGPT in collaborative learning environments.

2. Theoretical Background

2.1 ChatGPT

ChatGPT could be a game-changer in reshaping and revolutionizing the educational landscape [9], which is consistent with how ChatGPT present on its website as an AI-powered language model designed to support and engage in human-like conversations. However, ChatGPT is disrupting various disciplines within the education sector, raising concerns such as the potential for cheating, honesty and truthfulness, privacy misrepresentation, and manipulation risks [12].

As a research tool used for editorial support, ChatGPT contributes to more coherent writing in assignments that cover multiple aspects. For example, [13] points out that ChatGPT can generate coding solutions for typical college-level assignments. However, using AI-powered chatbots has raised alarms among practitioners who scrutinize the authenticity of student submissions. There are warnings that an overreliance on ChatGPT could diminish students' critical thinking skills [5].

The rise of AI-driven chatbots like ChatGPT has sparked discussions about the integrity of student work, and the current state of education is poised for significant change [14]. In the context of the social sciences, students' ability to consider multiple perspectives and produce comprehensive reports is a hallmark of achievement and maturity. Many educators encourage students to use tools such as Google to gather complete information, echoing the sentiment expressed by Isaac Newton: "If I have seen further, it is by standing on the shoulders of giants."

However, teachers may need help deciding whether to encourage using ChatGPT for assignments and learning. Using ChatGPT's summarizing and organizing capabilities as a research assistant can lead to complete work [14]. While humans may easily outperform AI in small-scale tests with concrete answers, AI may demonstrate expert-level performance in broader, more subjective assessments. This potential shift has created a complex discourse about the future of education as ChatGPT's role as a learning tool continues to evolve.

For instance, a study in South Korea on The rise of AI-driven chatbots like ChatGPT has sparked discussions about the integrity of student work, and the current state of education is poised for significant change [14]. In the context of the social sciences, students' ability to consider multiple perspectives and produce comprehensive reports is a hallmark of achievement and maturity. Many educators encourage students to use tools such as Google to gather complete information, echoing the sentiment expressed by Isaac Newton: "If I have seen further, it is by standing on the shoulders of giants."

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[15] conducted a parasitology examination with ChatGPT 3.0 and medical students, revealing that ChatGPT 3.0's interpretive abilities and correct judgments were currently lower than those of medical school students yet still maintained considerable accuracy. The study suggested that ChatGPT 3.0 has the potential to surpass medical students in the future, akin to how Deep Blue defeated the world chess champion. Likewise, [16] emphasized the computational advantages of ChatGPT in significantly advancing our understanding of climate change and improving the accuracy of climate forecasts. In the financial realm, [17] underscored the distinct benefits of ChatGPT in the finance sector, where data recognition is crucial. When users possess substantial domain expertise, ChatGPT can generate high-quality analyses. This advantage becomes particularly pronounced in tasks that require intensive data analysis and future predictions.

ChatGPT also functions as a learning tool, offering personalized support such as answering students' questions, assisting with assignments, and providing learning strategies. With AI capabilities, ChatGPT can respond to students' queries in real-time and tailor support based on individual needs and learning status. While ChatGPT has facilitated many conveniences, it has also sparked controversies and challenges, including data security, privacy protection, AI ethics, and the interaction between students and AI [18]. Earlier versions of ChatGPT questions for lacking originality and novelty in their generated output, but version 4.0 exhibited significant improvement. Concurrently, the growing debate over potential concerns, such as algorithmic biases, misinformation, ethical considerations, and information security, has intensified. This research seeks to explore these matters through the lenses of AMO theory and the Technology Acceptance Model.

2.2 AMO theory

[19] posited that individual job performance within an organization emanates from the intricate interplay between ability, motivation, and opportunity. Expanding on this premise, [20] delineated the constituents of employee ability (high skill), motivation (when appropriately stimulated), and job opportunities (involving employee participation and commitment) as catalysts for improved performance. His seminal work, [21] underscored that personal and organizational performance arise from the triadic interaction of ability, motivation, and opportunity, formalizing the AMO theory. Within the AMO framework, "ability" denotes an individual's competence to execute specific tasks, representing a fundamental prerequisite for performance. In educational contexts, this encompasses students' capabilities in acquiring new knowledge, honing problem-solving skills, cultivating critical thinking abilities, and more. "Motivation" serves as the impetus propelling an individual's pursuit of goals, with student motivation in the learning environment potentially driven by intrinsic factors (e.g., learning interests, passion for learning) and extrinsic motivators (e.g., rewards, pressures). "Opportunity" pertains to the circumstances or conditions enabling an individual to showcase his or her ability and motivation. In education, opportunities can encompass aspects such as the availability of learning resources, curated learning activities, teacher support, and the like [22].

The AMO model furnishes a multifaceted lens for evaluating learning, transcending mere assessment of students' current conditions to illuminate strategies and methods for augmenting learning outcomes. This insight can influence teachers' pedagogical efficacy [23]. For instance, strategizing to amplify students' learning competencies, invigorate their motivation, and proliferate learning opportunities can enhance learning performance. Exploring collaborative learning's effectiveness through the AMO framework, enriched further by tools like ChatGPT, enriches understanding of the collaborative learning dynamic and fine-tuning instructional methodologies.

2.3 TAM theory

The Technology Acceptance Model (TAM) proposed by [24] is an adaptation of the Theory of Reasoned Action (TRA) formulated by [25]. This model emphasizes the interplay between perceived ease of use and perceived usefulness, influencing users' attitudes. While perceived usefulness directly influences intention to use, perceived ease of use indirectly influences behavior through attitudes.

In reasoned action, individuals synthesize various pieces of information and carefully weigh the pros and cons, including customer needs. Integrating the principles of reasoned action, TAM explores technology users' attitudes and willingness to adopt technology, focusing on perceived usefulness and ease of use. Within the Technology Acceptance Model usage research field, this theory effectively predicts users' behavioral intentions. The link between actual behavior and intention to use is inseparable [26]. This link significantly shapes a user's propensity to perform a particular action, as emphasized [27].

TAM has five main components: External variables: These primarily influence perceived usefulness and ease of use and include factors such as the user's external environment, interface, organizational support, system design, convenience, and political and economic considerations. Perceived Ease of Use: The more accessible the information technology system is to learn and use, the more likely users will be more efficient and have greater confidence in their work performance and control. Perceived usefulness: This reflects the potential of a technology information system to enhance individual performance, increase work capacity, and subjectively increase work efficiency. Attitude toward use: This represents the user's positive or negative feelings about the information technology system. Both perceived usefulness and ease of use influence this attitude positively. Behavioral Intention to Use: This represents the user's willingness to use the information technology system, influenced by perceived usefulness, ease of use, and attitude toward use [28,29,30].

TAM provides a robust model that describes how external variables and individual perceptions influence the acceptance and use of technological systems. By analyzing the relationships between external variables, perceived ease of use, perceived usefulness, attitude toward use, and behavioral intention, TAM provides a comprehensive understanding of the use and acceptance of technology.

3. Research Methods

Based on the AMO theory, this study examines the educational application of ChatGPT and the consumer's intention to use it. The independent variable AMO in this study use measured in three sub-dimensions: ability, motivation, and opportunity (with five questions for ability, four questions for motivation, and five questions for opportunity), and the dependent variable TAM is composed of four constructs: perceived ease of use, perceived usefulness, attitude toward use, and behavioral intention to use. Five-item questionnaire for each construct. AMO primarily examines individual ability, motivation, and opportunity to use ChatGPT. At the same time, TAM focuses on aspects such as ease of use, level of help, attitude toward use, and intention to use ChatGPT among university students. All research constructs were measured using a five-point Likert scale. [31] Each construct should have at least three questionnaires, among which 5 to 7 questions are the best, and each construct of this research has five questionnaires. AMO theory has been widely applied in various fields. Initially, it was mainly used to measure performance indicators, such as exploring the relationship between gender and job performance [32] and the link between performance work systems and innovative performance in small and medium enterprises [33]. Subsequently, AMO theory has been used to measure and analyze various behaviors. These include the behavior of the Norwegian government toward new hydropower development [34], the behavior of African COVID-19 vaccination [35], the behavior of Chinese farmers engaged in organic farming [36], and the behavior of Indian household waste segregation [37]. Chinese research on the behavior of teenagers in ice sports [38], among others.

In recent years, this research has focused more on examining how AMO theory influences the Technology Acceptance Model (TAM). A search in WOS revealed 14 papers that combine AMO and TAM to study different behaviors. Examples include the behavior of Malaysian consumers in using e-wallets during the COVID-19 pandemic [39], the introduction of e-commerce in non-metropolitan areas of India [40], consumer behavior in using intelligent technology (IST) in the retail industry [41], Internet usage behavior studies in Malaysia [42], and selection behavior in beauty industry media platforms in Taiwan [43], Etc. In addition, during the COVID-19 period, there have been studies on students' adaptability to online activities and academic performance [44] and critical factors in emergency online university education [45]. The research shows that using AMO and TAM to study behavior is flourishing. Notably, this is the first paper to use CHATGPT to explore TAM from an AMO perspective. Based on the literature review, this research proposes the following hypotheses.

H1: Users of ChatGPT for collaborative learning will be positively and significantly influenced by AMO, which comprises ability (H1a), motivation (H1b), and opportunity (H1c).

H2: Users of ChatGPT for collaborative learning will experience a positive and significant influence of AMO on their attitude towards its use.

H3: Users of ChatGPT for collaborative learning will experience a positive and significant influence of AMO on their perceived ease of use.

H4: Users of ChatGPT for collaborative learning will experience a positive and significant influence of perceived ease of use on their attitude toward use.

H5: Users of ChatGPT for collaborative learning will experience a positive and significant effect of perceived ease of use on perceived usefulness.

H6: Users of ChatGPT for collaborative learning will experience a positive and significant influence of perceived usefulness on their attitude toward use.

H7: Users of ChatGPT for collaborative learning will experience a positive and significant influence of perceived usefulness on their behavioral intention to use.

H8: Users of ChatGPT for collaborative learning will experience a positive and significant influence of attitude toward use on behavioral intention to use.

H9: Users of ChatGPT for collaborative learning will experience an AMO exerting a significant positive influence on behavioral intention to use, mediated by attitude toward use.

H10: Users of ChatGPT for collaborative learning will experience an AMO that exerts a significant positive influence on behavioral intention to use, mediated sequentially by perceived ease of use and attitude toward use.

H11: Users of ChatGPT for collaborative learning will experience an AMO exerting a significant positive influence on behavioral intention to use, mediated sequentially by perceived ease of use and perceived usefulness.

H12: Users of ChatGPT for collaborative learning will experience an AMO exerting a significant positive influence on behavioral intention to use, mediated sequentially by perceived ease of use, perceived usefulness, and attitude toward use.

The study uses SmartPLS as the primary statistical analysis tool. SmartPLS emphasizes the quality indices that are traditionally utilized to evaluate the performance of the model in terms of explained variances [46]. First, path coefficients between different constructs were calculated using PLS-SEM, followed by bootstrapping with resampling of 5000 samples as the basis for data analysis and inference. According to [47] factor loadings between constructs and question items should exceed 0.7. The question item should be discarded to

ensure good item-construct validity if this is not achieved. [48] suggested that Cronbach's alpha and Rho_A internal consistency coefficients should be greater than 0.7 in a high-reliability range; if less than 0.7, they would be in an unacceptable low-reliability range. [49] suggest that composite reliability (CR) and average variance extracted (AVE) can be used to validate construct reliability. The internal consistency of construct indicators is represented by composite reliability (CR). According to [50], the composite reliability should approach or exceed 0.6, and the AVE should be greater than 0.5 to ensure convergent validity, thus demonstrating high reliability in each construct. Such an analysis allows survey items to infer latent variables more accurately.

4. Results and Discussion

<Table 1> Constructs reliability and validity analysis of reflective indicators

	Cronbach's α	Composite reliability (rho_a)	AVE	Items	Factor Loadings	T value	VIF
AMO	0.953	0.953	0.621				
AB	0.900	0.901	0.714	AB1	0.847	45.726	3.337
				AB2	0.818	30.069	2.754
				AB3	0.868	55.401	4.014
				AB4	0.834	42.305	2.831
				AB5	0.857	53.141	3.066
MO	0.923	0.925	0.813	MO1	0.932	84.587	4.813
				MO2	0.908	78.642	4.578
				MO3	0.900	73.870	3.193
				MO4	0.865	40.151	2.545
OP	0.899	0.901	0.714	OP1	0.875	67.104	3.314

				OP2	0.893	61.537	3.759
				OP3	0.859	51.309	2.753
				OP4	0.751	25.900	2.031
				OP5	0.838	37.545	2.290
PEOU	0.872	0.877	0.663	PEU1	0.850	45.268	2.519
				PEU2	0.860	42.196	2.970
				PEU3	0.743	21.915	1.719
				PEU4	0.810	30.420	2.199
				PEU5	0.804	34.332	1.993
PU	0.889	0.891	0.693	PU1	0.855	60.259	2.807
				PU2	0.811	22.229	2.252
				PU3	0.880	61.982	3.412
				PU4	0.790	26.776	2.197
				PU5	0.821	33.807	2.300
ATU	0.943	0.944	0.815	ATU1	0.811	45.792	2.942
				ATU2	0.902	72.225	4.067
				ATU3	0.854	77.161	3.778
				ATU4	0.885	72.578	4.744
				ATU5	0.833	60.068	3.493
BIU	0.910	0.915	0.736	BIU1	0.847	31.544	2.596
				BIU2	0.818	83.972	3.924
				BIU3	0.868	47.096	2.811
				BIU4	0.834	49.634	3.263
				BIU5	0.857	54.958	2.133

Note: AB = Ability; MO = Motivation; OP = Opportunity; AMO= Ability, Motivation, Opportunity; PEOU =Perceived Ease of Use; PU = Perceived Usefulness; ATU = Attitude Towards Use; BIU = Behavioral Intention to Use

In this study, we assessed the internal consistency of the items within the structure using Cronbach's α and composite reliability (CR) values. A Cronbach's α value or CR value greater than 0.7 is acceptable. In our research, the range of Cronbach's α values for each construct was 0.872 to 0.943, and the CR values were 0.877 to 0.944, indicating excellent internal consistency. [51] The factor loading of each item should be greater than 0.5. This study's factor loads of each item are more excellent than 0.75, which meets the standard.

The detailed data are shown in Table 1, the results of the tests for construct reliability and validity. The VIF values , as shown in Table 1, met the standard level suggested by [52].

To evaluate the validity of our instruments, we used the average variance extracted (AVE) as a measurement standard. It is recommended that the AVE value of each construct exceed 0.5. Our results show that the AVE values for the constructs ranged from 0.663 to 0.815, indicating that each facet has sufficient explanatory power [53].

We also examined the discriminant validity between the constructs. The square root of each construct's AVE value exceeded the correlation coefficients between that construct and other constructs, indicating good discriminant validity. In the confirmatory factor analysis, the factor loadings of all items for each construct were more significant than 0.7, indicating good convergent validity. The results of the reliability and validity analyses are shown in the table [54,55].

Discriminant validity in this study refers to the degree to which the underlying characteristics of different constructs are not highly correlated, indicating that the data between different quality constructs should show low degrees of correlation. Good discriminant validity between constructs means that there are clear and substantial differences between the variables of different constructs [50]; for proper discriminant validity, the square roots of the AVEs (the diagonal values) should be significantly greater than the inner construct correlations. Following this standard, all the diagonal scores in our study (which are the square roots of the AVE) are greater than their corresponding inter-construct correlations. Consequently, it can be concluded that the constructs in this research are distinct from each other and exhibit adequate discriminant validity [50]. Table 2 displays the square root of AVE (Average Variance Extracted) in the diagonal cells and the correlation between constructs in the off-diagonal cells. The square root of the AVE value for each construct is noticeably larger than the correlation among the hidden variables. The result shows that the constructs differ, demonstrating sufficient discriminant validity [50].

<Table 2> Discriminant Validity. The square value of the correlation coefficient between the constructs, an AVE between the constructs and their corresponding indicators

	Mean	SD	AB	MO	OP	PEOU	PU	ATU	BIU
AB	3.615	0.904	0.845						
MO	3.981	0.838	0.726	0.902					
OP	3.781	0.887	0.779	0.757	0.845				
PEOU	4.213	0.703	0.422	0.359	0.355	0.814			
PU	4.230	0.727	0.425	0.338	0.368	0.801	0.832		
ATU	4.162	0.778	0.447	0.433	0.418	0.803	0.790	0.903	
BIU	3.714	0.950	0.413	0.378	0.369	0.685	0.782	0.726	0.858

Note: AB = Ability; MO = Motivation; OP = Opportunity; PEOU =Perceived Ease of Use; PU = Perceived Usefulness; ATU = Attitude Towards Use; BIU = Behavioral Intention to Use; SD: Standard Deviation; Mean: Average.

Structural equation modeling (SEM) with SmartPLS 4 was used to validate the hypotheses in this study using 5,000 subsamples through the bootstrapping method. The significance of the path coefficients was determined using standard evaluations from the PLS-SEM literature. A model fit value of 0.074 met the good fit criteria of less than 0.08, as outlined by [56]. The d_ULS value of 6.370, which exceeds the upper limits of the confidence intervals, further supports the model's acceptability.

The study used Harman's one-factor test to address potential common method bias and conducted a post-hoc test for common method variance (CMV). The first factor explained 45.699% of the cumulative variance, which decreased to 28.439% after rotation, indicating that CMV was not a significant problem [57]. The study did not find a single factor that accounted for most of the variation, ruling out bias from common method variation.

Regarding path coefficients, ability, motivation, and opportunity function as first-order constructs of AMO. According to [58], second-order constructs should have at least three first-order constructs, a condition met by AMO. The first-order constructs in this model serve as reflective indicators of the second-order construct, requiring a moderate to high correlation between them.

In this study, ability, motivation, and opportunity had β values of 0.841, 0.806, and 0.860, respectively, with AMO, confirming a moderate to high correlation. Hypothesis 1 is supported. Regarding the path coefficients, there is a significant positive correlation between AMO to PEOU ($\beta = 0.416$, $t = 8.658$, $p < 0.000$), AMO to ATU ($\beta = 0.136$, $t = 4.286$, $p < 0.\ 000$), PEOU to PU ($\beta = 0.820$, $t = 38.061$, $p < 0.00$), PEOU to ATU ($\beta = 0.443$, $t = 6.581$, $p < 0.00$), PU to ATU ($\beta = 0.371$, $t = 5.515$, $p < 0.00$), PU to BIU ($\beta = 0.555$, $t = 10.289$, $p < 0.00$), and ATU to BIU ($\beta = 0.287$, $t = 4.901$, $p < 0.00$). Hypotheses 2 through 8 are all supported. This result not only re-prove the acceptance of the TAM model but also shows that AMO significantly impacts the TAM model. According to the path analysis results of the data in Figure 1, the paths are all positive and significant, which shows that this structural model has an excellent explanatory ability for the endogenous constructs discussed.

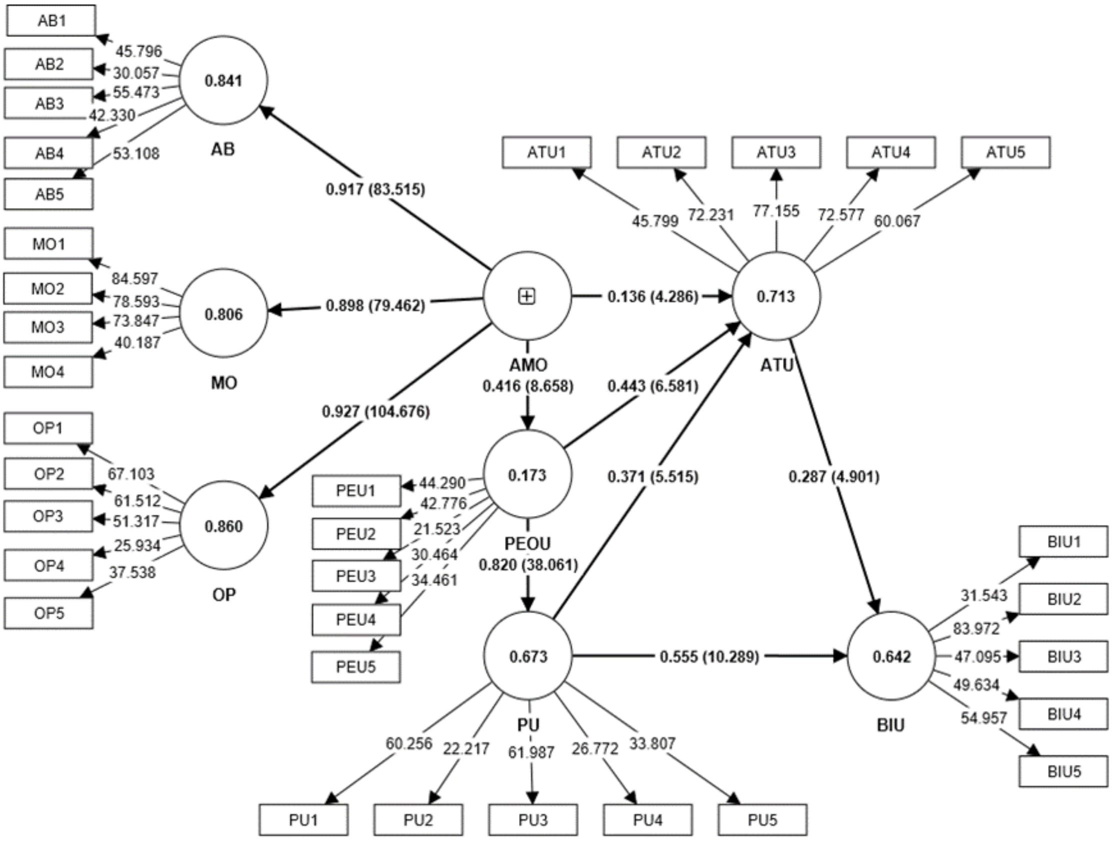

Figure1: Path coefficients, t-values , and square multiple correlations (SMC or R2)

The corresponding t value is used as the judgment basis. When the t value is greater than 0.05, the critical value of the significant level is 1.96. It means that the estimation of this variable has statistical significance. In addition, in the intermediary part, the previous TAM results were verified again, all T values were more significant than 1.96, and the minimum T value in the construct was 3.095, as shown in the table below. They construct a 95% bootstrap confidence interval for the difference in mean distances. This study extracts the central 95% of the results from the bootstrap distribution. Calculate the percentiles: The lower and upper bound do not contain 0, indicating a significant level [59]. Based on the path analysis of the data in Table 3, both the individual and intermediary paths are positive and significant. This result might show that AMO is the main factor influencing TAM.

<Table 3> Path Effect Test Results

Path	Original sample (O)	T Value	Decision
AMO -> AB	0.917	83.515	Supported
AMO -> MO	0.898	79.462	Supported
AMO -> OP	0.927	104.676	Supported
AMO -> ATU	0.136	4.286	Supported

AMO -> PEOU	0.416	8.658	Supported
PEOU -> ATU	0.443	6.581	Supported
PEOU -> PU	0.82	38.061	Supported
PU -> ATU	0.371	5.515	Supported
PU -> BIU	0.555	10.289	Supported
ATU -> BIU	0.287	4.901	Supported
AMO -> ATU -> BIU	0.039	3.126	Supported
AMO -> PEOU -> ATU -> BIU	0.053	3.8	Supported
AMO -> PEOU -> PU -> BIU	0.189	6.573	Supported
AMO -> PEOU -> PU -> ATU -> BIU	0.036	3.095	Supported
PEOU -> ATU -> BIU	0.127	4.195	
PEOU -> PU -> BIU	0.455	9.976	
PEOU -> PU -> ATU -> BIU	0.087	3.35	
PU -> ATU -> BIU	0.106	3.374	

5. Conclusions

This exploratory study investigates the impact of AMO (Ability, Motivation, Opportunity) on TAM (Technology Acceptance Model) in ChatGPT and its application to collaborative teaching. It is groundbreaking education research and marks a significant milestone in integrating AI-driven tools with traditional teaching methods.

AMO's impact on TAM. Ability: The ability to use ChatGPT depends on both technical skills and economic considerations. Whether a user can afford the subscription cost or effectively communicate with the system to achieve desired outcomes reflects their ability to use this software. Motivation: Internal and external motivations are essential to a user's intention to use ChatGPT. Driven by curiosity, innovation, and external rewards, users may show increased interest in using this tool. Opportunity: Opportunities such as training, support, and collaborative integration are critical factors in successfully adopting ChatGPT in teaching scenarios. Access to essential resources and a supportive environment will influence student attitudes toward its use.

The Technology Acceptance Model (TAM) emphasizes PEOU and PU. PEOU: ChatGPT is designed with an accessible interface that allows participation without high technical barriers, thus catering to a broad audience. PU: Compatibility with different platforms and tools increases the perceived usefulness of ChatGPT. Its strong data analysis capabilities support content creation and interactive learning, and its application in business could improve customer service. For people with disabilities or non-native English speakers, its usefulness is even more pronounced.

By integrating the AMO framework with the existing TAM structure, this study brings to light more implicit pathways that influence user attitudes and behaviors. It demonstrates the potential of ChatGPT to increase learning efficiency, engagement, and overall educational quality. Educators can consider AMO factors when integrating ChatGPT into their instructional practices.

[60] Using ChatGPT to enhance Sustainable Development Goals (SDGs) significantly improved the accuracy.[61] AI framework underscores the importance of a combined approach incorporating technological, pedagogical, and ethical knowledge to integrate AI into education effectively.[62] AI program's success drives plans to broaden AI literacy to senior students and the wider public. It serves as a model for diverse educational outreach. These scholars have proved that ChatGPT using AI will continue to have a sustainable impact on education. These scholars have proved that ChatGPT using AI will continue to have a sustainable impact on education. This research lays the groundwork for further exploration by educators, businesses, and policymakers alike. The relationship between ChatGPT and the collaborative teaching paradigm highlights new avenues for future research, including cultural considerations, long-term effects, or subject-specific influences. Comparative studies between traditional collaborative teaching methods and those supported by ChatGPT could provide even more insight.

In a world of rapidly advancing technology, understanding and harnessing the phenomenon of AMO-TAM alignment offers insights into broader societal implications. Just like [63] pointed out, ChatGPT may be a new wonder drug in the trial. Even if we cannot utilize it now, it will slowly and gradually influence our lives, just like search engines, social media, and so on. This study not only underscores the relevance of ChatGPT within the educational landscape but also suggests its potential applicability across diverse fields and demographics.

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