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Students' behavioral intentions toward generative AI in education: Task-technology fit and moral obligations

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Abstract

The rapid advancement of generative AI tools, such as ChatGPT, has sparked widespread debate over their impact on academic integrity and educational practices. As these tools become increasingly accessible to students, understanding the factors that influence their adoption in academic settings is essential. The current study explores the application of generative artificial intelligence (AI) tools by college students, such as ChatGPT and many others, for completing homework assignments. Drawing on the Task-Technology Fit (TTF) framework and the concept of moral obligation, this research aims to investigate the factors influencing students' behavioral intentions to use generative AI in academic contexts. Data were collected through an online survey of 136 Taiwanese college students. The results indicate that perceived technology characteristics and self-efficacy significantly enhance task-technology fit, positively affecting behavioral intention. Conversely, moral obligation shaped by perceived teacher attitudes negatively influences students' intention to use AI tools for coursework. The study employs Partial Least Squares Structural Equation Modeling (PLS-SEM) to test the hypotheses and explains a substantial proportion of the variance in behavioral intention. These findings provide theoretical insights into how technological and ethical considerations jointly influence AI adoption in education. The study also offers practical suggestions for educators and institutions aiming to guide the responsible use of generative AI in learning environments. This study contributes a novel framework for understanding responsible AI use in higher education.

Keywords: Behavior intention, ChatGPT, College students' attitude, Generative artificial intelligence, Moral obligation, Self-efficacy, Task-technology fit.

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Contribution of this paper to the literature
This study presents a novel dual-perspective model that integrates task-technology fit and moral obligation to explain students' use of generative AI in education. Unlike previous research, it demonstrates how perceived teacher attitudes influence moral obligations, thereby advancing the understanding of both AI adoption and ethical decision-making in academic settings.

1. Introduction

The term "generative AI" describes artificial intelligence applications that create text, vocal, or visual content, intending to produce original, creative, and novel content based on the data they have collected (Aydin & Karaarslan, 2023; Mannuru et al., 2023). Generative AI is rapidly evolving into a new digital era, which learns and mimics existing data patterns and creates new content, data, or information, including text, images, music, and more. The emergence of generative AI has caused substantial disruption, particularly in education (Lim, Gunasekara, Pallant, Pallant, & Pechenkina, 2023). The generative AI establishes capabilities beyond simple data analysis or prediction; it can unleash creativity and innovation in creative arts, content creation, personalized learning, and broader business domains.

Recently, academics and educators have seriously considered using AI for instruction, learning, and education assessment (Kohnke, Moorhouse, & Zou, 2023a, 2023b). Applying generative AI in the education field has sparked widespread and in-depth discussions.

Generative AI may help students generate content for learning activities, such as automatically writing code, literary works, and even academic assignments. It also initiates controversial arguments about academic integrity and intellectual property rights. Students might engage in academic dishonesty by submitting an assignment generated by AI instead of producing original work (Cotton, Cotton, & Shipway, 2024). These discussions touch upon the ethical and moral issues of using such generative AI tools and whether students should use generative AI, considering that education aims to foster student knowledge growth. Generative AI raises questions about whether it deprives students of learning opportunities and calls into question the value of education.

This paper explores the controversial issues of using generative AI in education, focusing on college students' behavioral intentions regarding the use of generative AI to complete coursework assignments. When discussing the adoption of new technology, task-technology fit influences its acceptance, while moral obligations are crucial considerations when addressing behaviors with ethical concerns. Therefore, the discussion of whether students adopt generative AI for assignment writing has two perspectives: whether generative AI, as a new technology, is suitable for this task (completing coursework assignments) and whether ethical considerations influence the adoption of generative AI.

Widely used, task-technology fit discusses whether a specific task suits new technology (Dishaw & Strong, 1999). Besides task characteristics, the factors influencing task-technology fit are perceived technology characteristics (Fu, Shang, Jeyaraj, Sun, & Hu, 2020). Users' self-efficacy in mastering the technology is crucial for perceiving the technology as fitting the task (Shahzad, Zhang, Zafar, Ashfaq, & Rehman, 2023).

Moral obligations refer to ethical considerations of whether students should or should not engage in certain behaviors (Regan, 2012). Literature indicates the association between teachers' and students' attitudes toward adopting Generative AI tools (Barrett & Pack, 2023). Students' intention to use generative AI in homework assignments may depend on teachers' attitudes. When teachers believe students should not use generative AI, they may form moral obligations against it.

This study employed quantitative methods to collect data through questionnaire surveys and utilized statistical analysis to evaluate the antecedents affecting generative AI. This study aims to offer an in-depth investigation of the application of AI in educational environments, exploring its potential and challenges in the field of education. This study attempts to address two research questions:

1. Will task-technology fit and moral obligation considerations affect students' intention to use generative AI for coursework assignments?
2. What are the underlying factors that shape the influence of task-technology fit and moral obligation in decision-making processes?

2. Hypotheses

The rapid development of AI, such as Large Language Models (LLMs) like ChatGPT, has recently sparked extensive discussion and attention in the global education community (Knekta, Runyon, & Eddy, 2019). Various learning activities have widely applied innovative AI tools. For instance, recent studies have indicated that generative AI tools can help students and educators automatically generate code, write literary works, and even compose complex academic reports and assignments. These advancements significantly improve learning efficiency and enable students to access and master more advanced knowledge and skills.

With the extensive application of generative AI technology in instruction, students and teachers have access to richer learning resources and tools, greatly enriching educational content and methods (Kamalov, Santandreu Calonge, & Gurrib, 2023). However, generative AI technologies bring about some critical ethical and legal issues (Schlagwein & Willcocks, 2023), particularly regarding academic integrity and ownership of creative works (Eke, 2023; Smits & Borghuis, 2022). Educators may like to know how to appropriately utilize AI tools as learning aids rather than relying solely on them to complete tasks and how to address and understand copyright issues related to content generated by artificial intelligence (McFarlane, 2019). These issues are sparking widespread discussions in the global education community and urging academic institutions, teachers, and students to seek solutions together.

2.1. Task-Technology Fit for using Generative AI on Assignments

College students must consider whether generative AI features suit a specific coursework assignment or term paper report. The task-technology fit (TTF) model can describe the fit between coursework assignments and generative AI in education. The TTF model, proposed by Goodhue and Thompson (1995), argues that the alignment between the demands of a task and the features of technology can predict the adoption of the technology and the performance of individuals. The literature revealed that task-technology fit could explain the use of educational technology (Bere, 2018; Lin, 2012; McGill & Klobas, 2009).

Task characteristic refers to the characteristics of the coursework assignment. For example, when the coursework assignments are about performing data analysis or statistical tasks, AI tools may quickly process data and provide accurate analysis results, significantly improving work efficiency. However, in coursework assignments that require creative thinking and original content, such as art creation, literary creation, theoretical argumentation, and many others, the coursework aims to provide opportunities to induce students' creative thinking and abilities to create original content. Although generative AI can still provide valuable outcomes, the nature of the coursework assignment is to exercise the process rather than obtain the results. Therefore, understanding the nature and requirements of coursework assignments and how to match the capabilities of generative AI to them is critical to improving student learning performance.

Generative AI models are intelligent and capable of simulating human thinking. However, they may also produce false information (Kim et al., 2023), inappropriate content (Rao et al., 2023; Ray, 2023), or even severe nonsense (Rudolph, Tan, & Tan, 2023), leading to misleading information (Metze, Morandin-Reis, Lorand-Metze, & Florindo, 2024) and untrustworthy (Banovic, Yang, Ramesh, & Liu, 2023). Generative AI can, for example, automatically produce content such as news articles, comments, and social media posts. This machine-generated content often blurs the line between human and artificial authorship, making it difficult to distinguish its origin. As a result, it may influence public opinion, compromise the credibility of information dissemination, and lead to misinformation and potential harm to the public interest. It is a severe issue in college education since students may not easily distinguish between AI-generated and accurate, reliable content. If students unquestioningly believe the answers given by generative AI, they may be misled and misbelieve. Therefore, educating students on identifying and verifying information sources is essential while emphasizing the importance of critical thinking and information literacy. Doing so enables students to assess whether generative AI tools are appropriate for a given assignment more effectively.

Generative AI tools can provide only partial support for students' learning activities. Therefore, educators should guide students in understanding the limitations of such tools and encourage them to integrate their critical thinking and analytical skills when using AI effectively. A task-technology fit is achieved when generative AI's capabilities align with the coursework assignments' requirements. The technical characteristics of generative AI include its ability to provide practical, accurate, and timely answers and outcomes to coursework assignments. Technology characteristics are critical to whether students are willing to adopt this technology.

Based on the preceding discussion, we propose the following two hypotheses:

H_1: The technology characteristics (TEC) of generative AI positively impact the perception of task-technology fit (TTF).

2.2. Self-Efficacy of using Generative AI

Self-efficacy refers to an individual's belief in their ability to perform the behaviors necessary to achieve specific performance goals (Bandura, 1977, 1986, 1997). Generative AI applications for learning have recently bloomed. However, students must know how to harness generative AI (Yilmaz & Yilmaz, 2023). They should be able to ask appropriate questions to generative AI applications to obtain the answers they seek. Unlike most software operated via a menu bar, generative AI tools, such as ChatGPT, are operated using prompts input through chat commands. Generative AI tools are powerful when users can provide appropriate prompts.

Students' ability to craft effective prompts is crucial for unlocking the full potential of generative AI tools. Therefore, they must develop the necessary skills to use these tools effectively. Thus, perceived self-efficacy in using generative AI may influence students' intention to use these tools (Liang, Wang, Luo, Yan, & Fan, 2023). When using generative AI, the more precise the instructions users give, the better its answers will be. Students' ability to use generative AI will directly affect their willingness to use it. Students who can effectively use generative AI tools will benefit significantly from quickly accessing and processing large amounts of information when conducting academic research, writing reports, or thinking creatively.

According to research by Joo, Park, and Lim (2018), self-efficacy is essential in the Technology Acceptance Model. Research shows that self-efficacy is a crucial factor affecting individuals' adoption and use of technology (Ariff, Yeow, Zakuan, Jusoh, & Bahari, 2012; Holden & Rada, 2011; Mun & Hwang, 2003). Based on the above discussion, the following hypothesis was proposed:

H_2: Students' self-efficacy (SE) assessment of using generated AI positively impacts task-technology fit (TTF) perception.

TTF is essential for information systems usage (Cane & McCarthy, 2009; Larsen, Sørebø, & Sørebø, 2009). It is expected to predict individuals' perceptions and behavioral intentions regarding technology use and the impact of technology on performance. According to Goodhue and Thompson (1995), technology must suit the tasks it supports. Individuals are more likely to adopt a technology when they perceive a good task-technology fit. The relationship between task-technology fit and behavioral intention to use various information systems has been well established in prior research, such as social networking sites (Lu & Yang, 2014) online learning (Lin, 2012; Wu & Chen, 2017; Yu & Yu, 2010) learning management systems (McGill & Klobas, 2009) e-commerce (Klopping & McKinney, 2004) online banking (Rahi, Khan, & Alghizzawi, 2021) mobile banking (Changchun, Haider, & Akram, 2017) and many others. Therefore, the study proposes the following hypothesis:

H_3: The perception of task-technology fit (TTF) positively impacts students' behavioral intention (BI) to adopt Generative AI.

2.3. Generative AI and Academic Integrity

Academic integrity is an issue that needs to be taken seriously in academia, and the content generated by generative AI has always been controversial regarding academic integrity. Whether the AI-generated content is original is another issue requiring in-depth discussion.

There are diverse perspectives regarding the use of generative AI in learning and coursework assignments. Ibrahim, Asim, Zaffar, Rahwan, and Zaki (2023) pointed out that generative individuals may also employ AI for academic dishonesty. Currie (2023) believes that using generative AI to write coursework is an act of plagiarism. They argued that some students might improperly use AI-generated content to complete coursework and fail to find the correct source of citation, which may lead to plagiarism issues. Jarrah, Wardat, and Fidalgo (2023) argued that using generative AI to produce content without proper citation constitutes plagiarism, as the generated content is not considered original work. However, they also argued that if AI-generated content is properly rewritten, critically analyzed, and correctly cited, it should not be considered plagiarism. Kasneci et al. (2023) proposed that generative AI is useful for students. Generative AI can help students promote their ideas and provide inspiration. It can also provide students with customized teaching, such as exercises to test their knowledge or coursework suggestions, which will help their learning process. In the context of teaching, generative AI can support educators in various tasks (Kaplan-Rakowski, Grotewold, Hartwick, & Papin, 2023; Vartiainen & Tedre, 2023; Verma, Campbell, Melville, & Park, 2023). It can provide teachers with ideas for teaching plans, allowing teachers to offer students more diversified instruction.

In educational practice, generative AI has become a tool for students to cope with coursework, causing schools to pay attention to this issue.

Students' moral obligation may affect their behavioral intention for using generated AI (Schlagwein & Willcocks, 2023). When students believe these tools are morally right, they may be more intent on using them. Pursuing what people think is right and acting on that belief constitutes a moral obligation. In the current study, moral obligation refers to students' views on using generative AI for coursework assignments. Beck and Ajzen (1991) believe that students' moral obligations can explain whether students will engage in academic dishonesty. Students' moral obligation to use generative AI for assignments reflects students' academic ethics. Therefore, students' moral sense of using generative AI for assignments may impact their behavioral intentions for using generative AI. Students who have a moral obligation not to use generative AI in coursework assignments may consider it an act of academic dishonesty, with originality controversy, and feel guilty when using generative AI.

Drawing upon the above discussion, the following hypothesis is proposed:

H_4: Moral Obligation (MO) positively impacts students' intention (BI) to adopt generated AI in assignments.

2.4. Perceived Teacher's Attitude

Teachers' attitudes may influence students' attitudes (Gelişli, 2007). When students perceive that their teachers hold positive attitudes toward using generative AI in coursework assignments, they will also believe it is acceptable to use generative AI in coursework assignments. By contrast, when students perceive their teachers' negative attitudes toward using generative AI in coursework assignments, they will perceive a moral obligation not to use it.

Given the ongoing debate surrounding the use of generative AI in education, teachers are likely to hold differing opinions regarding students' use of such tools for coursework. Chiu (2023) noted that some educators explicitly prohibit students from using generative AI to complete their assignments. They worry that students will reduce their capacity for critical thinking and creativity after using it. However, other teachers are more open-minded and willing to change students' learning models, encouraging students to use generative AI for learning. They believe that generative AI is helpful for learning and can improve learning outcomes. As a result, teachers' attitudes toward generative AI will influence students' intention to use it.

Under social cognitive theory, individuals tend to model their behavior on the attitudes of influential others, such as authority figures and role models (Bandura, 1986). Teachers are role models for students (Lumpkin, 2008; San-Martín, Fernández-Laviada, Pérez, & Palazuelos, 2021; Shein & Chiou, 2011; Yazigi, Nasr, Sleilaty, & Nemr, 2006). It is a reasonable inference that teacher attitudes significantly impact students' learning motivation and behavioral intentions toward educational technology. Students may view the teacher's attitude as a guideline for behavior, thereby affecting their judgment of correct behavior. Accordingly, this study posits that students who perceive their teachers as supportive of generative AI tools will develop a more substantial moral obligation to their use. Further, when teachers support the use of generative AI tools, students may feel morally obligated to follow this pattern of behavior, thus enhancing their behavioral intention in using generative AI tools.

Based on the above discussion, the study proposes the following hypothesis:

H_5: Students' perceived teacher's attitude (PTA) positively impacts their moral obligation (MO) perception.

The research model is shown in Figure 1.

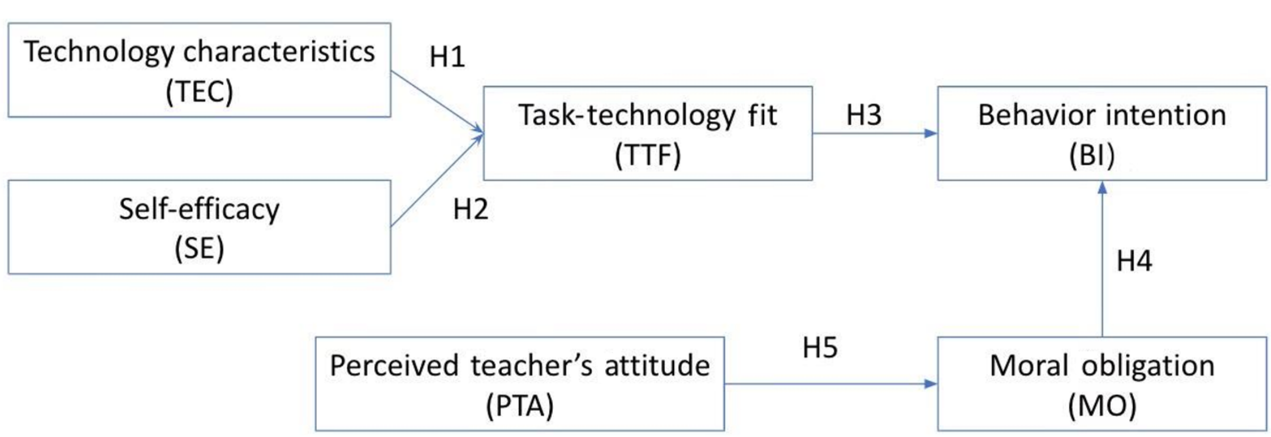

Figure 1. Research model.

3. Methodology

3.1. Subjects

This study employed an online questionnaire survey to examine the perspectives of Taiwanese college students regarding the use of generative AI tools (e.g., ChatGPT) in completing their coursework assignments. The study used Facebook ads to recruit respondents who voluntarily and anonymously participated in this study.

In the current study, participants were not minors, prisoners, aborigines, pregnant women, individuals with physical illnesses, or individuals with mental illnesses. They were not improperly intimidated or unable to make decisions of their own free will. The studies in the current article were non-registered, non-interactive, and nonintrusive research conducted in public and online spaces. The study did not and could not collect information to identify specific individuals. This study was exempted from Institutional Review Board approval as per the Food & Drug Administration, Ministry of Health and Welfare, Taiwan, Order No. 1010265075, as the participants did not meet specified criteria for subjects mandating such review, were subjected to no medical interactions or interventions as a result of the study, and cannot be recognized individually from the data published.

The Facebook ads attracted 1,040 views. Among them, 365 respondents filled out the questionnaire. Respondents could only complete the questionnaire once. Of these respondents, 160 were college students, while 205 were not. This study included only college students as samples. From the 160 college student samples, 24 were excluded due to missing data or low-quality responses, such as selecting the same answer for all questions or providing inconsistent responses to reverse-scored questions. The final sample size was 136. The study offered incentives, including a lottery for ten US$3 cash prizes and ten mobile phone holders. The questionnaire survey was conducted from November 5, 2023, to November 11, 2023.

Participants in this study were not recruited from a single college, university, or any specific institution. Instead, the respondents were voluntarily recruited through Facebook advertisements and represented a diverse group of Taiwanese college students from multiple institutions. Furthermore, none of the respondents were students, acquaintances, or friends of any of the authors. This recruitment approach was designed to ensure respondent anonymity and enhance the representativeness and objectivity of the data collected.

Among the 136 respondents, 59 (43.4%) were male, and 77 (56.6%) were female. 106 (77.9%) were full-time students, and 30 (22.1%) had jobs. Among the respondents, 6 (4.4%) were 18 years old, 98 (72.1%) were 19-25 years old, 11 (8.1%) were 26-30 years old, and 12 (8.8%) were 31-40 years old. Nine respondents (6.6%) were over 41 years old.

3.2. Procedure

This study's data collection process was divided into two parts. In the first part of the questionnaire, using Likert-type scales, participants responded to measurement items related to technology characteristics, task-technology fit, self-efficacy, perceived teacher attitudes, moral obligation, and behavioral intention. The second part gathered demographic information, such as gender and age.

Detailed measurement scales are listed in Appendix 1, and discussed as follows.

3.2.1 Task-Technology Fit

The current study developed a three-item scale to measure the task-technology fit of AI tools in course assignments based on the seven-item scale proposed by Erskine, Khojah, and McDaniel (2019). Item statements were revised to match the scenario of generative AI.

3.2.2 Technology Characteristics

Zhou, Lu, and Wang (2010) developed a three-item scale to measure technology characteristics. Gan, Li, and Liu (2017) revised the scale of Zhou et al. (2010) to measure three technology characteristics of real-time, reliable, and convenient mobile learning services. In the current study, we also developed a three-item scale based on the scales of Gan et al. (2017) and Zhou et al. (2010) to measure the technology characteristics of generative AI tools. Three characteristics, robustness, efficiency, and reliability are measured on the technology characteristics scale of the current study.

3.2.3 Self-Efficacy

In the study, self-efficacy is the students' self-assessment of their ability to use generative AI. Kim, Suh, Lee, and Choi (2010) developed a three-item scale to measure the self-efficacy of information systems, as described by Taylor and Todd (1995). The current study developed a three-item scale based on Kim et al. (2010) to measure students' self-efficacy with generative AI tools.

3.2.4 Perceived Teachers' Attitude

The attitudes of those around them influence individuals' behavior. In academic learning, teachers' attitudes toward generative AI tools play a critical role in shaping students' intentions to use such tools for completing coursework assignments. Dix, Emery, and Le (2014) developed a nine-item model to measure students' perceived social norms regarding academic integrity. Among these nine items, two focus on teachers' attitudes. The current study adopts these two items and adds a new item to measure perceived teachers' attitudes toward using generative AI tools for coursework assignments.

3.2.5 Moral Obligation

Beck and Ajzen (1991) revealed that students' dishonest actions are related to their moral obligations. They developed a three-item scale to measure students' moral obligation to cheat on a test or exam. Cronan, Mullins, and Douglas (2018) revised the three-item scale to measure students' intention to cheat on coursework assignments. The current study revises the three-item scale to measure students' moral obligation to use formative AI tools on coursework assignments.

3.2.6 Behavior Intention

Beck and Ajzen (1991) used a three-item scale to measure individuals' intention to cheat on tests or exams. Kam, Hue, and Cheung (2018) also used this three-item scale to measure students' intention to engage in academic dishonest behavior. The current study developed a three-item scale to measure behavioral intention to use generative AI tools for coursework assignments based on the scale developed by Beck and Ajzen (1991).

4. Analysis and Results

The current study employed multi-item scales to assess students' perceptions of various factors, including technology characteristics, self-efficacy, task-technology fit, behavioral intention, moral obligation, and perceived teacher's attitude. To evaluate the reliability of these measurement scales, Cronbach's α and composite reliability (CR) were calculated. As shown in Table 1, Cronbach's α values are 0.667 for technology characteristics, 0.870 for self-efficacy, 0.819 for task-technology fit, 0.866 for behavioral intention, 0.865 for moral obligation, and 0.825 for perceived teacher's attitude. The composite reliability coefficients are 0.687, 0.874, 0.826, 0.872, 0.866, and 0.849 for the respective constructs. All Cronbach's α and CR values exceed 0.70, except for technology characteristics, which has a Cronbach's α of 0.667 and a CR of 0.678. Both values are close to the threshold of 0.7. Overall, the Cronbach's α and composite reliability coefficients indicate acceptable or marginally acceptable reliability for the measurement scales, supporting their use in the study.

Table 1. Cronbach's alpha, composite reliability, average variance extracted, and R^2.

Construct	Items	Factor loading	Cronbach's alpha	Composite reliability (CR)	Average variance extracted (AVE)	R^2
Technology characteristics (TEC)	TEC1 TEC2 TEC3	0.838 0.782 0.702	0.667	0.678	0.602	
Self-efficacy (SE)	SE1 SE2 SE3	0.863 0.921 0.888	0.870	0.874	0.793	
Task-technology Fit (TTF)	TTF1 TTF2 TTF3	0.905 0.834 0.830	0.819	0.826	0.735	0.421
Behavior intention (BI)	BI1 BI2 BI3	0.859 0.905 0.899	0.866	0.872	0.789	0.636
Moral obligation (MO)	MO1 MO2 MO3	0.897 0.879 0.888	0.865	0.866	0.788	0.423
Perceived teacher's attitude (PTA)	PTA1 PTA2 PTA3	0.874 0.815 0.888	0.825	0.849	0.739	

This study assessed convergent validity by examining each construct's average variance extracted (AVE). The AVE coefficients for technology characteristics, self-efficacy, task-technology fit, behavioral intention, moral obligation, and perceived teacher's attitude are 0.602, 0.793, 0.735, 0.789, 0.788, and 0.739, respectively. The results showed that all the constructs' AVE values were above the cutoff value of 0.5 suggested by Fornell and Larcker (1981) and Straub, Boudreau, and Gefen (2004). Therefore, we confirmed the acceptable convergent validity of the measurement scales.

Fornell and Larcker (1981) assessed discriminant validity by comparing the square root of the average variance extracted (AVE) for each construct with its correlations with other constructs. As shown in Table 2, the square roots of all AVEs are greater than the corresponding inter-construct correlation coefficients, indicating that the measurement scales used in this study demonstrate satisfactory discriminant validity.

Table 2. Correlation and Average Variance Extracted.

Construct	Technology characteristics	Task-technology fit	Self-efficacy	Perceived teacher's attitude	Moral obligation	Behavior intention
Technology characteristics	0.776					
Task-technology fit	0.590	0.857				
Self-efficacy	0.347	0.459	0.891			
Perceived teacher's attitude	-0.161	-0.397	-0.263	0.860		
Moral obligation	-0.173	-0.549	-0.353	0.644	0.888	
Behavior intention	0.298	0.652	0.373	-0.413	-0.65	0.888

Note: The average variance extracted (AVE) square roots are on the diagonal.

This study employed Partial Least Squares Structural Equation Modeling (PLS-SEM) to test the research hypotheses. PLS-SEM is widely used to examine the interrelationships among variables and is particularly suitable for studies with relatively small sample sizes. Given that the sample size in this study is 136, PLS-SEM was deemed appropriate for the analysis.

The study evaluated hypotheses with path coefficients and R^2 values within the PLS-SEM framework. Path coefficients indicate the strength and direction of the relationships between independent and dependent variables; they are expected to be statistically significant and aligned with theoretical expectations. R^2 values represent the proportion of variance in the dependent variables explained by the independent variables, thereby reflecting the model's explanatory power (Hair, Anderson, Tatham, & Black, 1987).

Table 1 reveals that R^2 for behavior intention is 0.626, indicating that the model explains 62.6% of the variance in behavior intention. The high R^2 suggests that the proposed research model can explain most of the variance in behavior intention. The R^2 for task-technology fit is 0.421, indicating that technology characteristics and self-efficacy explain 42.1% of the variance in task-technology fit. The R^2 for moral obligation is 0.423, indicating that perceived teachers' attitudes explain 42.3% of the variance in moral obligation. The results of the PLS-SEM structural model show that the selected variables can explain most of the variance of the dependent variables.

The PLS-SEM analysis results are shown in Figure 2. The model shows that both technology characteristics (coefficient = 0.493, t=7.449, p<0.001) and self-efficacy (coefficient = 0.279, t=3.719, p<0.001) have positive effects on the task-technology fit. Besides, the perceived teacher's attitude positively affects moral obligation (coefficient = 0.650, t=14.324, p<0.001). Task-technology fit positively influences behavioral intention (coefficient = 0.385, t = 5.489, p < 0.001). Moral obligation negatively influences behavioral intention (coefficient = -0.520, t = -7.578, p < 0.001). According to the PLS-SEM analysis results, all five hypotheses were confirmed. The study concluded that students' behavioral intention to use generative AI on coursework assignments is determined by the perceived task-technology fit of using generative AI on coursework assignments and students' perception of moral obligation. Perceived task characteristics and perceived self-efficacy are antecedents of task-technology fit. Perceived teacher's attitude is an antecedent of moral obligation.

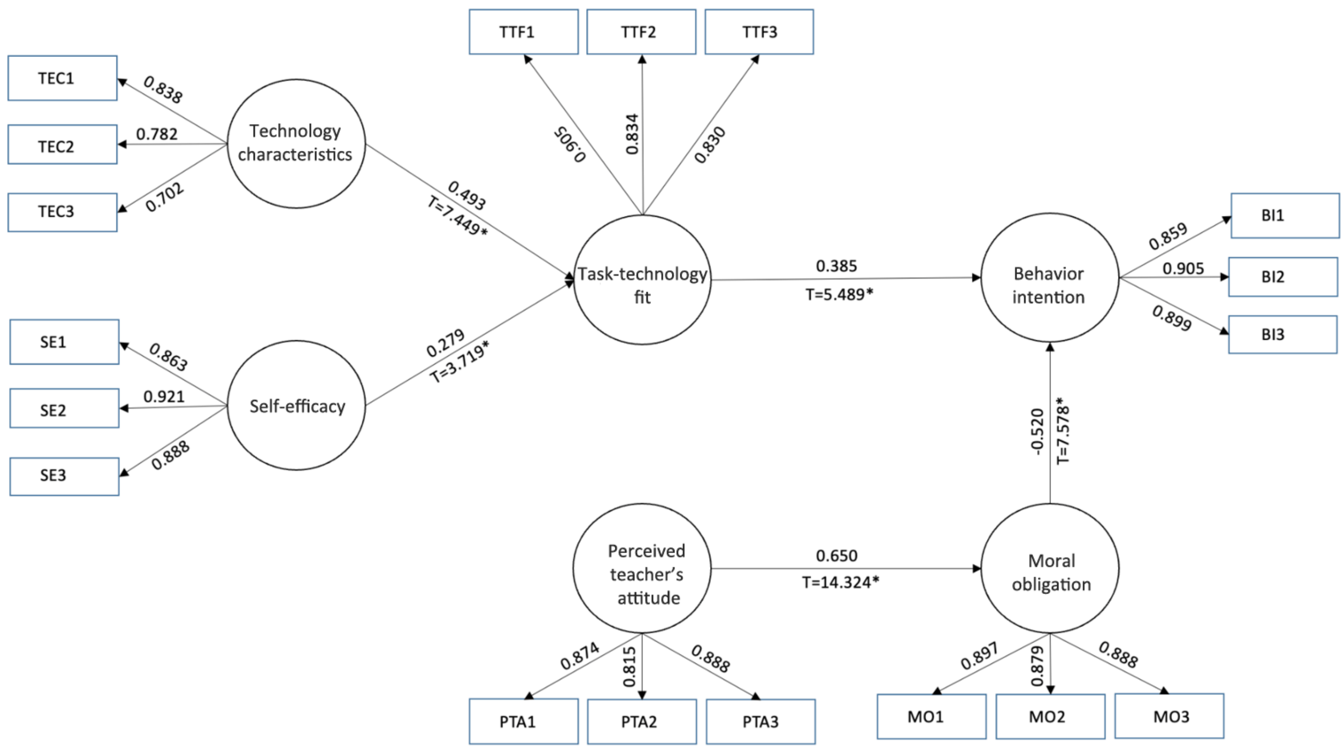

Figure 2. Model results.

Note: *P<0.05.

5. Conclusion

This study investigates the behavioral intentions of Taiwanese college students toward using generative AI tools (such as ChatGPT) for assignments. The results indicate that technology characteristics, self-efficacy, task-technology fit, and moral obligation significantly impact students' behavioral intentions. Additionally, perceived teachers' attitudes significantly positively influence their moral obligations. These findings highlight the multifaceted nature of students' intentions to use generative AI tools, emphasizing the influence of both individual and contextual factors in educational environments (Van Den Berg & du Plessis, 2023).

5.1. Research Contribution

This research reveals the critical factors influencing students' adoption of generative AI tools, especially regarding technology characteristics, self-efficacy, and task-technology fit. These findings offer new insights into using generative AI tools in contemporary academic settings and provide valuable implications for educational policy and teaching practices. The study underscores the significance of moral obligation in upholding academic integrity and educational ethics. The results are an important reference for shaping instructional policies, informing curriculum design, and guiding the ethical integration of generative AI tools in teaching and learning. Through this research, a deeper understanding of academic responsibility and ethical awareness has been achieved, laying the groundwork for future educational innovation in the era of AI.

5.2. Practical Suggestions

Due to the impact of task-technology fit, schools should be committed to providing more advanced Generative AI tools to students to facilitate students' learning, thus promoting the development of schools in a more adaptive education direction. Besides, since self-efficacy positively impacts task-technology fit, schools should focus on students' self-efficacy training for using Generated AI, so that students can appropriately use Generated AI in learning.

Third, task-technology fit has a significant positive impact on students' behavioral intentions. Therefore, when teachers design courses where generative AI is used in teaching, they should consider whether the tasks are suitable for generative AI to ensure that students can fully utilize the value of generative AI and maximize the benefits of learning in the application of generative AI.

Fourth, moral obligation positively impacts behavioral intention. Therefore, in college education, students' awareness of academic integrity and moral obligation should be strengthened, and rules for generative AI should be formulated to help students use generated AI. When submitting assignments, adherence to principles of academic integrity and moral obligation is essential.

Finally, the positive impact of perceived teachers' attitudes on moral obligation is supported. Therefore, schools should provide teachers with courses or workshops on generative AI. Allow teachers to better understand the generative AI tool, enable it to serve as an auxiliary tool for grading coursework, and offer suggestions for areas that can be improved in students' coursework.

5.3. Research Limitations and Future Research Suggestions

While this study offers valuable insights, it is not without limitations. The following areas warrant attention in future research efforts.

First, the subjects of this study were Taiwanese college students. They have similar educational backgrounds and may not represent student groups from all cultural backgrounds. Future researchers may consider collecting data from different locations and using students from different cultural backgrounds as data samples to compare with this study to verify whether there are differences.

Second, self-reported data were used, which may be influenced by subjectivity and response bias. Third, this study did not thoroughly examine potential differences in students' use of generative AI tools across various academic disciplines. Future research could adopt more diversified approaches, such as mixed-methods designs integrating quantitative and qualitative data, to better understand students' behavioral intentions.

Fourth, this study did not explore whether using generative AI helps students learn, including teaching teachers how to incorporate generative AI into teaching. Future research can conduct educational interventions and explore how to effectively integrate AI tools into education systems, including teacher training and curriculum design.

Finally, generative AI tools may sometimes provide incorrect answers or inappropriate outcomes. As a result, some students may lack trust in the results of the AI generative tools and consider generative AI useless for learning. Therefore, educators should focus on integrating the use and understanding of generative AI into the curriculum so that students can better recognize the advantages and limitations of these technologies and learn how to apply them effectively.

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Appendix 1. Measurement items.

Variables	Items used in the current study	Adapted from
Task-technology fit	– The functionalities of generative AI tools are adequate for the homework assignments given. – The functionalities of generative AI tools help solve the homework assignments given. – The functionalities of generative AI tools make homework assignments easy.	Erskine et al. (2019)
Technology characteristics (TEC)	– Generative AI tools are efficient. – Generative AI tools are powerful. – Generative AI tools are reliable.	Gan et al. (2017) and Zhou et al. (2010)
Self-efficacy	– I am comfortable using generative AI tools without trouble. – I can use ChatGPT and generative AI tools well on my own. – I can familiarly use generative AI tools even if no one can help me.	
Moral obligation	– I would feel guilty if I used ChatGPT and other generative AI tools on my course term paper homework. – Using ChatGPT and other generative AI tools on my homework assignments goes against my principles. – It would be morally wrong to use ChatGPT and other generative AI tools on my homework assignments.	Cronan et al. (2018)
Perceived teacher's attitude	– My teachers would view me negatively if I used generative AI tools for homework assignments. – My teachers think it is essential not to use generative AI tools for homework assignments. – My teachers think using generative AI tools in homework assignments is strictly prohibited.	
Behavior intention	– I would use generative AI tools on homework assignments if I had the opportunity. – I would never use generative AI tools on homework assignments. – I may use generative AI tools on homework assignments in the future.	Beck and Ajzen (1991) and Kam et al. (2018)