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Exploring teacher adoption of AI: A structural analysis of Microsoft Copilot in education

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Abstract

This study aims to investigate the driving factors influencing teachers' intention to adopt an AI-powered assistant (Microsoft Copilot) in their professional development. This study attempted to validate ten hypothetical assumptions derived from notable theoretical models (UTAUT and TPACK). A survey was conducted with 280 teachers, who responded through Google Forms. The data were analyzed using Generalized Structured Component Analysis (GSCA) to test the proposed research model. The findings showed that both Technological Pedagogical Knowledge (TPK) and Perceived Ease of Use (PEOU) had a significant impact on teachers' self-efficacy and their intention to use Copilot. PEOU also played a key role in influencing Perceived Usefulness (PU) and Teaching Self-Efficacy (SE) while TPK directly affected PU and Behavioral Intention (BI). Interestingly, and somewhat unexpectedly, PU did not show a meaningful influence on either SE or BI. These results suggest that how easy a tool is to use and how well it fits into teachers' existing pedagogical knowledge may matter more than how useful it appears on the surface. Our proposed model explains 55.9% of the variation in the data. The study's findings are expected to make important contributions to the academic and practical aspects of applying AI to enhance teachers' digital competence.

Keywords: AI copilot, Professional development, STEM, Structural equation modeling, TPK.

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Contents

Contribution of this paper to the literature
This study uniquely integrates TAM, TPACK, and SCT to model teachers' adoption of Microsoft Copilot, revealing that perceived usefulness negatively impacts behavioral intention — a surprising divergence from prior assumptions. By combining technological and psychological factors, it offers a more holistic explanation of AI adoption in educational professional development contexts.

1. Introduction

Artificial intelligence (AI) is being widely applied in all areas of life from healthcare, insurance and finance to education and research with the development of science and technology in the era of big data (Chuyen, 2023; Vinh, Phung, & Cuong, 2024; Zawacki-Richter, Marín, Bond, & Gouverneur, 2019). One of the key factors driving this explosion is the emergence and development of pretrained models (Devlin, Chang, Lee, & Toutanova, 2019). These models have significantly shortened the time to perform many tasks from months, even years, to just a few hours or days. AI can now support us in doing those tasks instead of having to manually type each command or edit each detail. Pretrained models are models that have been trained on very large data sets and are mainly developed by large companies, due to the high requirements for computing resources and input costs. Each model is usually trained on a specific knowledge domain and optimized for each type of task, so there are currently many pretrained models published on the Internet, both free and paid (Wang, Li, Wu, Hovy, & Sun, 2023). Figure 1 depicts the evolution of pretrained models over time.

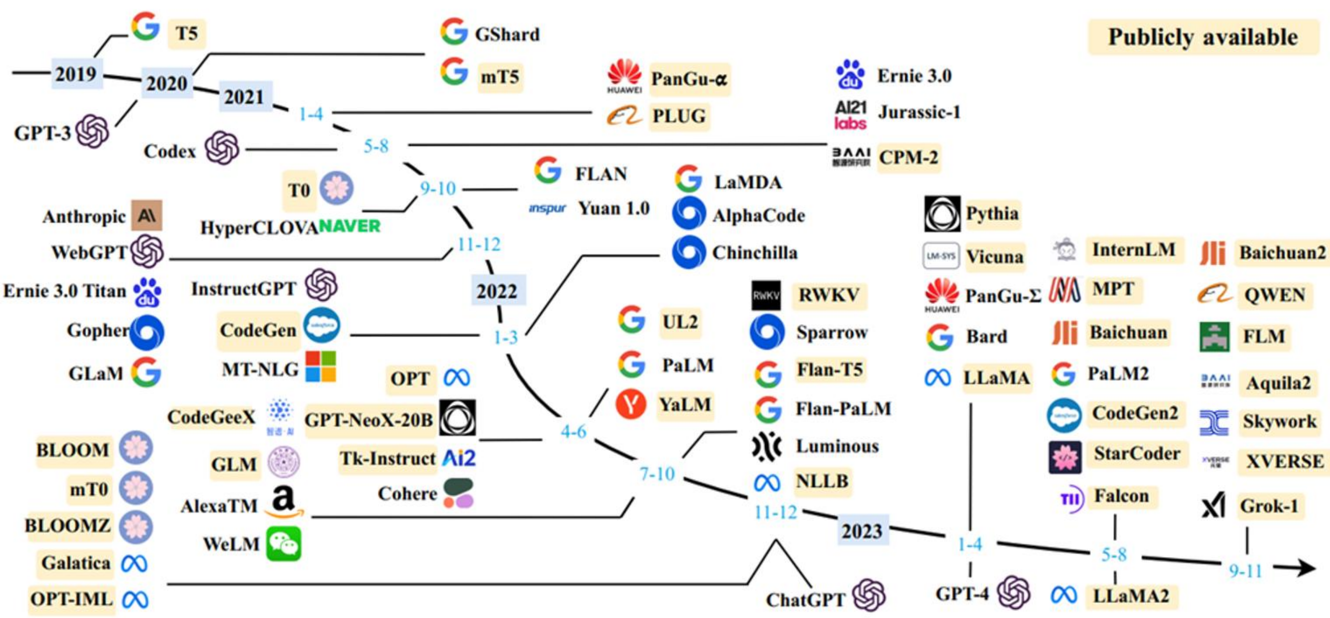

Figure 1. Evolution of pre-trained models

Although AI brings many benefits to users, it is also facing many challenges. The first challenge is the phenomenon of "hallucination" that is, creating new content that is not in the domain knowledge base (Wang et al., 2023; Wang et al., 2024). Most existing AI services recommend that users should consider the results generated by AI carefully because AI can give incorrect answers. The next challenge is the accessibility of AI to users. Some models only allow users from certain countries, which causes an unequal "divide" in technology. The third is the ability to understand and use AI effectively. Not all users can understand the capabilities that AI can bring, especially for those limited by language and technology barriers. For example, AI models trained on English datasets are not capable of communicating in other languages or how users should prompt the AI to give the desired answer.

Researchers and practitioners proposed several applicable approaches to shorten the gap between AI and users to alleviate the aforementioned issues (Nikolic et al., 2024; Vinh et al., 2024; Zawacki-Richter et al., 2019). For example, ChatGPT and other similar models provide a few templates (example questions) for users to start with while some other models present users with demo products for each use case. Companies like Google and Microsoft start integrating AI-powered functions directly into their applications (Adetayo, Aborisade, & Sanni, 2024; Stratton, 2024). This approach is expected to be highly effective due to "using AI in a specific context", but empirical evidence of its effectiveness is still limited (Chuyen, 2023; Hazzan-Bishara, Kol, & Levy, 2025). Most of the current beneficiaries of AI are from the business sector where there is a clear financial incentive to train employees to use AI. Many other organizations have yet to catch up with this trend. Education is a prime example where teachers are often limited in teaching time and must solve many problems for many students (Nemorin, Vlachidis, Ayerakwa, & Andriotis, 2023; Zha, Li, Wang, & Xiao, 2025). Therefore, accessing and using AI effectively is still a big challenge for many teachers, especially those with limited English and IT skills (Nazaretsky, Mejia-Domenzain, Swamy, Frej, & Käser, 2025). This is a very urgent issue that needs to be studied extensively, and solutions found together. According to UNESCO, integrating AI into education is no longer a luxury but an urgent issue especially in the context of teachers facing high workloads, administrative burdens and personalized learning (Kim & Kwon, 2023). Research to understand the relationship between factors and teachers' intention to use AI is critically important.

Thus, the purpose of this study is to address the above problem by investigating the factors influencing the intention to utilize Microsoft Copilot for teacher professional development. More precisely, the study proposes and empirically evaluates a conceptual model that integrates both technological and psychological determinants, such as perceived usefulness (PU), perceived ease of use (PEOU), technological pedagogical knowledge (TPK), teaching self-efficacy (SE), and behavioral intention (BI). These factors are derived from the Technology Acceptance Model (TAM), the Technological Pedagogical Content Knowledge (TPACK) framework, and Social Cognitive Theory

(SCT). No study has examined teachers' intentions to use AI-assisted tools for professional development by considering factors from the TAM (Davis, 1989), TPACK (Mishra & Koehler, 2006) and SCT (Tschannen-Moran & Hoy, 2001) models in this experiment. Most existing studies emphasize either technological determinants or psychological factors separately, lacking a comprehensive view that accounts for both aspects at the same time. The findings are expected to inform school administrators, educational policymakers, and teacher training programs about how to better support teachers in leveraging AI copilots effectively

The rest of this article is structured as follows: Section 2 underpins the theoretical background and hypothesis proposal. Next, section 3 discusses research design and methodology. Section 4 outlines the findings. Section 5 provides discussions and implications. Section 6 concludes the study and highlights future research directions.

2. Literature Review

2.1. The Role of AI Copilots in Education

The trend of AI in education has been investigated significantly, especially opportunities and applications for personalized learning, content generation, learner analytics, and teacher support (Ouyang & Jiao, 2021; Zawacki-Richter et al., 2019). Popular AI-powered tools like Microsoft Copilot, ChatGPT, Khanmigo, and Google Bard are gradually being integrated into educational settings to help teachers and students (Adetayo et al., 2024; Stratton, 2024). Among the various options available, Microsoft Copilot is starting to gain attention due to its ability to integrate directly into frequently used products teachers (e.g., Word, Excel, and PowerPoint). Similarly, researchers highlighted the benefits of AI-powered tools. For example, in supporting instructional design, delivering real-time feedback, and promoting teacher well-being by reducing burnout (Ali, Murray, Momin, Dwivedi, & Malik, 2024; Walter, 2024; Wang, King, Chai, & Zhou, 2023).

However, teachers' ability and level of use of these AI tools vary, such as familiarity with the technology, pedagogical flexibility, and confidence in using AI-driven systems (Zha et al., 2025). Previous research on AI in the social domain focused primarily on opportunities, challenges, concepts, and potential applications, with limited empirical research on specific factors influencing teachers' adoption of AI assistants (Wang et al., 2023). As a result, findings have focused on several factors, such as usability, data privacy, institutional infrastructure, and alignment with instructional goals (Ouyang & Jiao, 2021). Furthermore, existing studies often consider technological or psychological variables in isolation, without providing a comprehensive view of how these factors interact to shape behavioral intentions.

To address this issue, we identify and assess the technological and psychological determinants that influence teachers' intentions to adopt an AI-assisted tool (specifically, Microsoft Copilot) for professional development. To achieve this goal, we draw on what we believe to be important elements from prominent models, such as the Technology Acceptance Model (TAM), Technological Pedagogical Content Knowledge (TPACK), and Social Cognitive Theory (SCT).

2.2. Theoretical Framework and Hypothesis Development

2.2.1. Perceived Usefulness (PU)

Davis defined perceived usefulness (PU) as the degree to which a user believes a particular system enhances their job performance (Davis, 1989). Within the scope of this study, PU reflects how beneficial teachers find Microsoft Copilot in supporting their teaching tasks and instructional productivity. Recent studies reported that AI-powered tools can improve lesson planning, accelerate material preparation, and enhance instructional quality (Hazzan-Bishara et al., 2025). The current study includes PU as an indicator to evaluate Copilot's impact on teaching efficiency, expedite material preparation, and lesson planning quality.

2.2.2. Perceived Ease of Use (PEOU)

Perceived ease of use (PEOU) refers to how much a user believes that interacting with a system will be easy and straightforward (Davis, 1989). This factor has been a long-standing determinant in the successful integration of technology in educational settings. Here, PEOU conceptualizes how easily teachers can learn, use, and navigate Microsoft Copilot, particularly whether they find it intuitive and manageable without needing much outside guidance (Xu, Chen, & Zhang, 2024). Given the assumptions that many teachers may have limited technical training, this determinant becomes especially significant.

2.2.3. Technological Pedagogical Knowledge (TPK)

TPK reflects teachers' capacity to apply technological tools with pedagogy in instructional settings based on the Technological Pedagogical Content Knowledge (TPACK) framework (Mishra & Koehler, 2006). In the current research, TPK measures teachers' capacity to integrate Microsoft Copilot in lesson creation, tool selection, and content personalization (Mishra, Warr, & Islam, 2023). A strong grasp of TPK plays a pivotal role in determining teachers' readiness to use AI tools in authentic educational settings.

2.2.4. Teaching Self-Efficacy (SE)

According to Bandura's (2023) social cognitive theory , teaching self-efficacy is a well-established construct for measuring teachers' belief in their ability to influence student outcomes. Within this study, SE emphasizes trust of teachers in their ability to effectively utilize AI-powered tools, such as Microsoft Copilot despite potential technical issues or trying new technologies (Sumandal, 2023; Tschannen-Moran & Hoy, 2001). Teachers who believe in their pedagogical competencies are generally more proactive in trying and adopting new educational technologies.

2.2.5. Behavioral Intention (BI)

In the Technology Acceptance Model (TAM), behavioral intention (BI) serves as a crucial determinant in forecasting real-world use of actual technology usage. In this study, BI refers to teachers' anticipated actions to adopt Microsoft Copilot in their instructional practices, such as sustained usage and advocacy to colleagues (Hazzan-Bishara et al., 2025; Nikolic et al., 2024; Xu et al., 2024). Measuring BI helps estimate the potential impact and scalability of AI adoption in education.

The conceptual model proposes the following hypotheses:

H_1: Technological Pedagogical Knowledge (TPK) has a positive effect on Perceived Ease of Use (PEOU).
H_2: Technological Pedagogical Knowledge (TPK) positively influences Teaching Self-Efficacy (SE).
H_3: Perceived Ease of Use (PEOU) positively affects Teaching Self-Efficacy (SE).
H_4: Perceived usefulness (PU) significantly affects Teaching Self-Efficacy (SE).
H_5: Technological Pedagogical Knowledge (TPK) positively affects Perceived Usefulness (PU).
H_6: Perceived Ease of Use (PEOU) positively influences Perceived Usefulness (PU).
H_7: Technological Pedagogical Knowledge (TPK) positively influences Behavioral Intention (BI).
H_8: Perceived Ease of Use (PEOU) positively influences Behavioral Intention (BI).
H_9: Teaching Self-Efficacy (SE) positively influences Behavioral Intention (BI).
H_{10}: Perceived usefulness (PU) positively influences Behavioral Intention (BI).

According to Figure 2, the conceptual model was shaped by the hypotheses using ellipses to denote latent variables and arrows to depict assumed causal relationships.

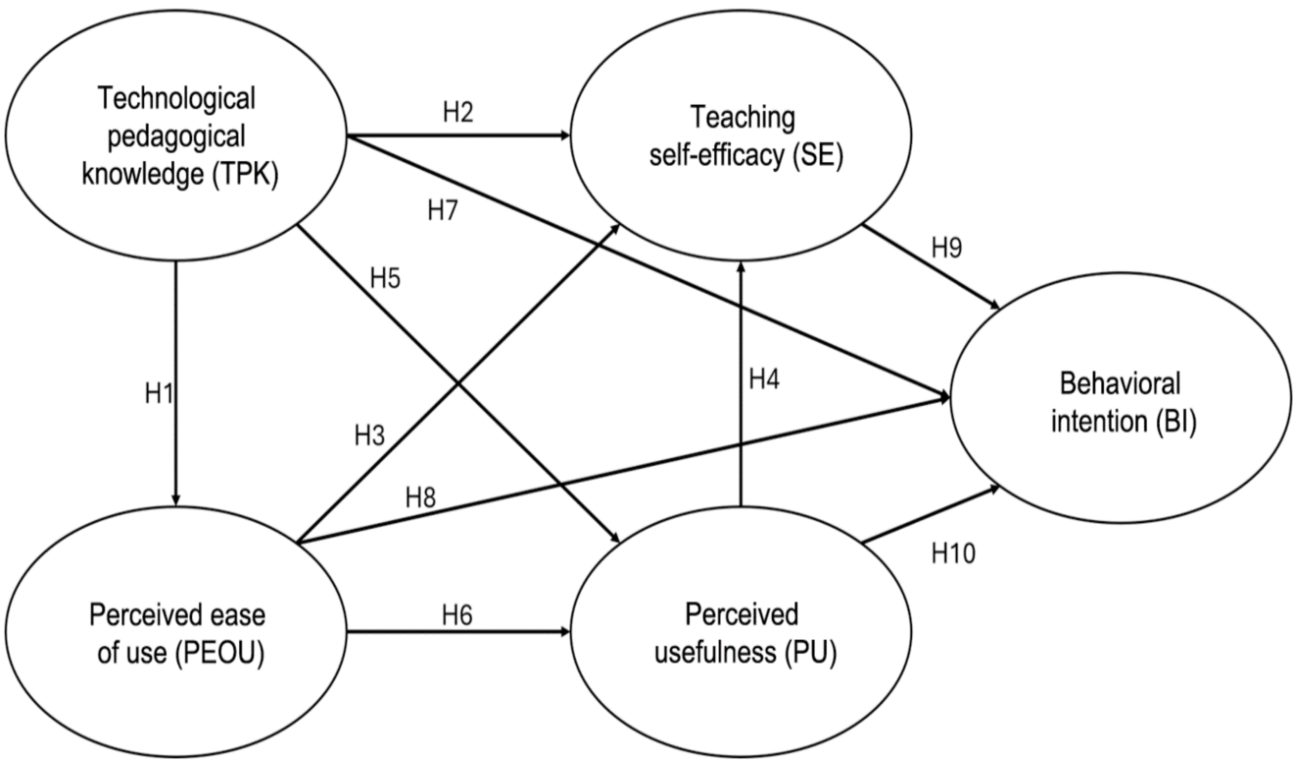

Figure 2. The proposed conceptual model.

3. Materials and Method

The next subsections outline the procedures for data collection, measurement, and analysis used to assess the conceptual model shown in Figure 2.

3.1. Data Collection

The study relied on a non-probability sampling method, specifically purposive sampling to gather participants. To reach participants, the researchers designed a structured survey using Google Forms and distributed it across various online spaces, including professional and educational communities and social media channels like Zalo and Facebook.

The survey was first distributed to teachers who were then encouraged to pass it along to other eligible participants following a snowball sampling procedure. This research was conducted at Vinh University, Vinh City, Vietnam.

Participants comprised teachers from the primary through high school levels who either had experience with digital learning tools or recognized Microsoft Copilot as an AI-enhanced instructional resource. The questionnaire was divided into two primary parts: (a) demographic details including gender, age, teaching level, frequency of digital tool usage, and level of exposure to Microsoft Copilot. (b) 23 items assessing five constructs on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). This study achieved 280 complete responses, exceeding the standard minimum requirement of 200 cases for conducting SEM in models of average complexity (Kline, 2023).

Institutional Review Board Statement: The Ethical Committee of Vinh University, Vietnam approved this study on 01/01/2025 (Ref. No. B2025-TDV-08).

3.2. Measures

The measurement tool consisted of 23 indicators corresponding to five key constructs: Perceived usefulness, perceived ease of use, technological pedagogical knowledge, teaching self- efficacy, and behavioral intention. Each latent variable was measured by a set of observed indicators.

The items were adapted from established instruments in previous studies and modified to fit with the context of Microsoft Copilot. Table 1 presents the specific items used in the questionnaire, organized by construct with their corresponding sources from the literature.

Table 1. Constructs and items

Construct	Item code	Item description	Sources
Perceived usefulness (PU)			
1	PU1	Using Microsoft Copilot improves my teaching efficiency.	Hazzan-Bishara et al. (2025)
2	PU2	Microsoft Copilot helps me prepare teaching materials more quickly.	
3	PU3	Microsoft Copilot enhances the quality of my lesson planning.	
Perceived ease of use (PEOU)			
1	PEOU1	Learning to operate Microsoft Copilot is easy for me.	Xu et al. (2024)
2	PEOU2	My interaction with Microsoft Copilot is clear and understandable.	
3	PEOU3	I find Microsoft Copilot easy to use.	
4	PEOU4	It is easy for me to become skillful at usingMicrosoft Copilot.	
5	PEOU5	I can effectively use microsoft copilot without much assistance.	
Technological pedagogical knowledge (TPK)			
1	TPK1	I know how to integrate Microsoft Copilot into lesson plans.	Mishra et al. (2023)
2	TPK2	I can select appropriate Copilot features to support my teaching.	
3	TPK3	I can design effective learning activities with the help of Microsoft Copilot.	
4	TPK4	I can use Microsoft Copilot to adapt content to student needs.	
5	TPK5	I understand how Copilot can enhance technology-based pedagogy.	
Teaching self-efficacy (SE)			
1	SE1	I am confident in my ability to use AI tools in teaching.	Sumandal (2023) and Tschannen-Moran and Hoy (2001)
2	SE2	I feel capable of solving problems that arise when using Microsoft Copilot.	
3	SE3	I believe I can successfully use Copilot to enhance my instruction.	
4	SE4	I am comfortable experimenting with new AI tools in the classroom.	
5	SE5	I feel self-assured when integrating Microsoft Copilot into my teaching.	
Behavioral intention (BI)			
1	BI1	I intend to use Microsoft Copilot in my teaching practice.	Xu et al. (2024)
2	BI2	I will frequently use Microsoft Copilot in the near future.	Nikolic et al. (2024)
3	BI3	I plan to incorporate Microsoft Copilot into future lesson planning.	Xu et al. (2024)
4	BI4	I am likely to recommend Microsoft Copilot to other educators.	Hazzan-Bishara et al. (2025)
5	BI5	I will continue using Microsoft Copilot if it is made available.	Xu et al. (2024)

3.3. Data Analysis

The collected responses were analyzed using Structural Equation Modeling (SEM) to validate the theoretical framework. SEM is widely recognized for its ability to model and assess causal relationships among several constructs in a single analytical framework (Kline, 2023). There are several ways to perform Structural Equation Modeling (SEM) depending on the research purpose and data characteristics. Among the most commonly used approaches are Covariance-Based SEM (CB-SEM), Partial Least Squares (PLS-SEM), and Generalized Structured Component Analysis (GSCA). This study adopted the GSCA approach. It provides a reliable framework for assessing the measurement model and the structural paths. Another reason that makes fits this study is its ability to work with a small sample size and not follow the normal distribution assumption (Hwang et al., 2021). Indicator weights, standard errors, and confidence intervals were used to validate the measurement model. Path coefficients and R-squared values were evaluated in the structural model to determine the explanatory power and significance of the proposed relationships.

4. Results

After data collection, a screening process was performed to ensure the quality of responses. 85 surveys were eliminated due to signs of insincerity (choosing the same option for all questions) and 47 items were eliminated due to missing data or incomplete filling.

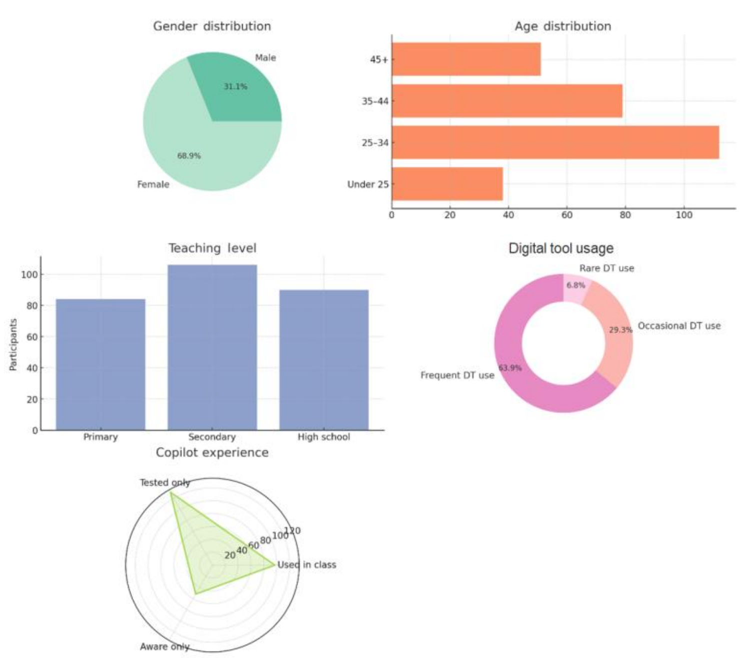

Figure 3. Overview of study participants, including gender distribution, age, teaching level, digital tool usage, and exposure to Microsoft Copilot.

After the data cleaning step, the total number of valid responses remaining was 280 accounting for approximately 70% of the total initial responses. This study exceeded the minimum threshold of 200 samples that is often recommended for SEM models of moderate complexity (Mardia, Kent, & Taylor, 2024) thereby ensuring the reliability of subsequent analyses with an actual sample size of 280.

Figure 3 presents the study participants' data through five different types of visual charts. The gender distribution shows that there is a predominance of females over males. In terms of age, the majority of teachers are in the 25-34 age groups. The data on the teaching level shows that the highest proportion is lower secondary school teachers, followed by upper secondary and primary school teachers. The level of digital tool usage reflects that the majority of teachers use technology regularly in their teaching. Finally, the graph showing the level of exposure to Microsoft Copilot shows that the majority of participants have used or experienced this tool, thereby demonstrating their willingness to approach AI-based teaching support solutions.

4.1. Quantitative Analysis

Descriptive data for the observed variables in the study showed that the mean values ranged from 3.614 (PU2) to 4.125 (PEOU3), indicating that the majority of participants tended to agree with the statements related to the use of Microsoft Copilot in teaching. The standard deviation ranged from 0.614 to 0.875 reflecting a moderate level of variation among responses. Regarding distribution, most variables had skewness and kurtosis within the ±2 threshold, specifically skewness from -1.046 to 0.12 and kurtosis from -0.85 to 2.119. This showed that the data had approximately normal distribution which was consistent with the requirements of analytical methods such as GSCA, which do not strictly require normal distribution conditions. Some variables, such as BI2 have higher skewness and kurtosis than the average but are still within acceptable limits, not significantly affecting the quality of model analysis.

Table 2. Construct quality measures

Indicators	TPK	PEOU	SE	PU	BI
PVE	0.501	0.67	0.666	0.633	0.608
Alpha	0.751	0.876	0.875	0.71	0.834
Rho	0.834	0.91	0.909	0.838	0.884

Table 2 presents the scale quality assessment indexes including PVE, Cronbach's alpha and composite reliability (Rho) for the five main constructs in the model. All PVE values are greater than 0.5 (from 0.501 to 0.67), indicating that the observed variables explain well the variance of the latent variables, ensuring convergent validity. Cronbach's alpha ranges from 0.71 to 0.876 while Rho ranges from 0.834 to 0.91, both exceeding the recommended threshold of 0.7, confirming the internal reliability and composite reliability of the scales. In general, the measurement constructs in the study meet the reliability requirements and can be used for subsequent structural model analyses.

Table 3. Factor loadings

Items	Estimate	SE	95%CI	
Technological pedagogical knowledge (TPK)				
TPK1	0.652	0.042	0.567	0.733
TPK2	0.724	0.029	0.667	0.794
TPK3	0.725	0.033	0.645	0.778
TPK4	0.707	0.037	0.63	0.767
TPK5	0.73	0.035	0.66	0.792
Perceived ease of use (PEOU)				
PEOU1	0.806	0.027	0.767	0.86
PEOU2	0.813	0.023	0.764	0.868
PEOU3	0.833	0.021	0.799	0.875
PEOU4	0.89	0.014	0.865	0.919
PEOU5	0.744	0.032	0.668	0.798
Teaching self-efficacy (SE)				
SE1	0.824	0.021	0.792	0.872
SE2	0.768	0.028	0.715	0.814
SE3	0.867	0.02	0.829	0.905
SE4	0.811	0.026	0.762	0.86
SE5	0.808	0.029	0.752	0.859
Perceived usefulness (PU)				
PU1	0.808	0.028	0.754	0.856
PU2	0.777	0.032	0.711	0.834
PU3	0.8	0.032	0.739	0.857
Behavioral intention (BI)				
BI1	0.856	0.018	0.822	0.89
BI2	0.855	0.018	0.821	0.89
BI3	0.82	0.037	0.743	0.867
BI4	0.711	0.058	0.565	0.791
BI5	0.629	0.052	0.504	0.706

Table 3 shows the factor loadings of the questions in the survey corresponding to the five main groups of variables of the study. Most of the questions have high loadings, mostly above 0.7. This is considered a good threshold in quantitative research. For the TPK group, items from TPK2 to TPK5 are all at a good level with TPK1 being a bit lower (0.652) but still within the acceptable range. The questions in the PEOU group are more prominent, especially PEOU4 with a coefficient of up to 0.89 showing that the participants have very consistent responses in this group. The SE group also gives quite strong results with high coefficients, above and below 0.8. The three questions in the PU group are also stable with no question being too low. In the BI group, there is a slight difference. The first four questions are quite good while BI5 is much lower (0.629) although not too low, it should still be considered when analyzing further. All of these coefficients have a 95% confidence interval that does not contain zero, which means they are statistically significant.

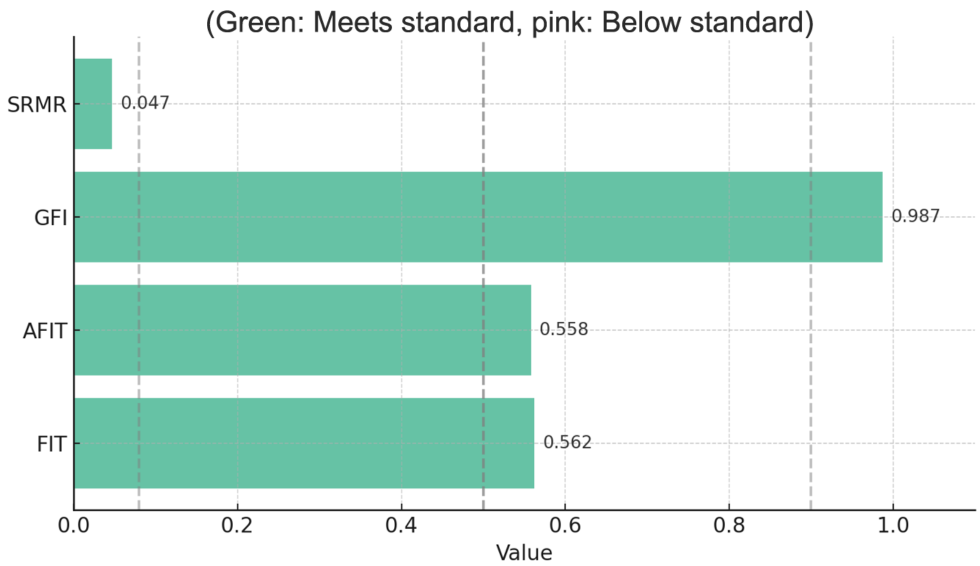

Figure 4. Model fit measures

Data from Figure 4 shows that the model has a relatively good fit. The FIT (0.562) and AFIT (0.558) indices both exceed the threshold of 0.5, reflecting that the relative explanation level of the model is acceptable. The GFI has a very high value (0.987) far exceeding the threshold of 0.9 indicating that the model fits the observed data well. The SRMR is 0.047 lower than the threshold of 0.08 indicating that the remaining deviation between the model and the data is very small. All indices meet or exceed the standard indicating that the research model has a high fit and can be used to test hypotheses in the next analysis step.

Table 4. Heterotrait-monotrait ratio of correlations

Correlations	Value	SE	95%CI	
TPK ↔ PEOU	0.689	0.05	0.554	0.788
TPK ↔ SE	0.786	0.045	0.664	0.886
TPK ↔ PU	0.566	0.086	0.337	0.733
TPK ↔ BI	0.701	0.046	0.58	0.794
PEOU ↔ SE	0.705	0.045	0.596	0.804
PEOU ↔ PU	0.563	0.062	0.322	0.69
PEOU ↔ BI	0.71	0.045	0.617	0.816
SE ↔ PU	0.438	0.084	0.252	0.592
SE ↔ BI	0.781	0.038	0.701	0.856
PU ↔ BI	0.307	0.082	0.149	0.48

Table 4 shows the level of discrimination between pairs of latent variables in the model. According to the commonly recommended threshold, HTMT should be less than 0.85 (some studies suggest a maximum of 0.90) to ensure sufficient discriminant validity between concepts (Joseph, Barry, Rolph, & Rolph, 2010; Mardia et al., 2024). The results show that most pairs of variables have HTMT values below this threshold. Specifically, relationships, such as TPK – SE (0.786), PEOU – SE (0.705), SE – BI (0.781) or TPK – BI (0.701) all show a close relationship but still maintain reasonable discrimination between concepts. Some pairs have significantly lower values, such as PU – BI (0.307) or SE – PU (0.438) indicating lower correlations, further strengthening the discriminant validity. No pair exceeded the threshold of 0.85. All 95% confidence intervals did not reach the threshold of 1.0 which confirmed that the constructs in the model met the requirements of discriminant validity.

Table 5. Path coefficients

Hypothesis	Estimate	SE	95% CI	
TPK→PEOU	0.562	0.046	0.468	0.645
TPK→SE	0.422	0.068	0.272	0.55
PEOU→SE	0.387	0.065	0.279	0.532
PU→SE	-0.001	0.058	-0.114	0.114
TPK→PU	0.236	0.077	0.096	0.381
PEOU→PU	0.318	0.06	0.206	0.435
TPK→BI	0.166	0.051	0.07	0.258
PEOU→BI	0.309	0.059	0.21	0.428
SE→BI	0.416	0.058	0.323	0.543
PU→BI	-0.113	0.045	-0.193	-0.021

The path coefficient table (see Table 5) provides a direct view of the relationship between the variables in the model. First, TPK strongly influences PEOU with a coefficient of 0.562 indicating that when teachers have good technology pedagogical knowledge, they tend to find tools like Microsoft Copilot easier to use. TPK also has a significant impact on SE (0.422) and PU (0.236), which makes sense because technology-savvy teachers are more confident and more likely to see the benefits of the tool. PEOU not only influences PU (0.318) but also SE (0.387) and BI (0.309). Perceived ease of use plays a significant mediating role in the model. When a tool is easy to use, teachers not only find it useful but also feel more confident in using it which leads to actual intention to use it. SE → BI has the highest coefficient in the entire table (0.416) confirming that self-efficacy is a key factor in driving AI tool usage behavior. On the contrary, a somewhat surprising result is that PU → BI is negative (-0.113) and statistically significant, meaning that when teachers feel that the tool is useful, they are less likely to use it. This could be an interesting paradox that deserves further discussion. Finally, PU does not significantly affect SE (the coefficient is close to 0) suggesting that perceived usefulness does not help much in making teachers feel more confident.

5. Discussion

5.1. Theoretical Implications

One of the most notable findings of this study is that the proposed model explained 55.9% of the variance in behavioral intention. This is a relatively high number showing that the model combining technological factors (TPK, PEOU and PU) and psychological factors (SE) is completely suitable in the context of research on teaching support tools such as Microsoft Copilot. Most of the tested hypotheses were confirmed. Self-efficacy (SE) emerged as the factor that most strongly influenced the intention to use (BI) with a coefficient of 0.416. In other words, when teachers feel confident in their own abilities, they will be more willing to apply AI tools in teaching (Tschannen-Moran & Hoy, 2001). In addition, perceived ease of use (PEOU) also plays a quite important role when it significantly affects both PU and SE. When a tool is easy to use, teachers not only feel it is useful but also feel more confident in using it. In addition, TPK also has a significant impact on PEOU, which makes sense teachers who are technologically and pedagogically savvy are much more likely to adopt and use AI tools (Mishra et al., 2023).

However, not all hypotheses were confirmed. A rather surprising result was that Perceived Usefulness (PU) did not have a significant impact on SE, and even had a negative impact on BI ($\beta = -0.113$). This goes against many previous studies where PU is often a strong influencer of intention to use (Davis, 1989; Venkatesh, Morris, Davis, & Davis, 2003). A plausible explanation is that teachers may find an AI tool like Copilot "useful" but do not yet see its practical value or relevance to their daily teaching work. Furthermore, perceived usefulness does not necessarily mean that they feel confident enough to use the tool, especially if they have language barriers or are unfamiliar with the technology (Sumandal, 2023).

This finding suggests that more support is needed to build teachers' skills and confidence so that they are truly ready to implement the tool in the classroom rather than simply emphasizing the usefulness of AI in education. Nevertheless, this study makes two important contributions: (1) confirming many of the relationships in existing theoretical models, and (2) highlighting unproven connections, especially the ambiguous role of PU – something that future research needs to explore further (Hazzan-Bishara et al., 2025; Xu et al., 2024).

5.2. Practical Implications

From a practical perspective, this study provides some important implications for integrating AI technology into educational environments. First, developers of teaching support tools, such as Microsoft Copilot should pay special attention to user-friendliness and pedagogical relevance. The results of the study show that PEOU and TPK are two factors that have a significant impact on the intention to use. Therefore, it is extremely necessary to design tools that are easy to use, accessible, and closely related to the needs of practical lesson planning.

Second, professional development programs for teachers should focus on improving technology pedagogical competence (TPK). This not only helps teachers better understand the functions of Copilot but also supports them in knowing how to effectively integrate this tool into their lessons. This can be done through forms, such asspecialized training, organizing sharing sessions between colleagues, or implementing group lesson design activities.

Third, although the research results show that perceived usefulness (PU) does not directly affect the intention to use, this does not mean that PU is not important in practice. On the contrary, for teachers to truly accept and use the tool, administrators and developers should clearly convey the practical value of the AI tool in improving the quality of the classroom and improving student learning outcomes. An effective way could be to share success stories or real-life experiences from teachers who have applied it. When insiders speak up, trust is easier to form than any promotional message.

5.3. Limitations

Although this study makes significant contributions, there are some limitations that need to be acknowledged. First, the data were collected through a non-probability sampling method, so the results cannot be absolutely representative of the entire teacher community across different regions and grade levels. The survey sample, although adequate in number may not fully reflect the diversity in real-life educational contexts. Second, the study was conducted using a cross-sectional design and relied primarily on self-reported intentions from participants, rather than measuring actual usage behavior. Therefore, it is not possible to conclude with certainty whether teachers actually use Copilot in the classroom. Future longitudinal studies will be needed to track trends in usage behavior over time. Third, the current model does not consider potential mediating variables such as trust in technology, school support, or previous experience using AI. These may help explain why perceived usefulness (PU) has a negligible or even negative effect on some relationships. Future studies should extend the model to include these factors to provide a more complete and in-depth view. Finally, the study focused on only one specific tool, Microsoft Copilot. Although Copilot is representative of the group of integrated AI tools in education, the results may be different if the model is applied to other AI platforms or tools with different features, interfaces, or pedagogical goals. Therefore, future comparative studies are needed to test the stability of the model across different contexts and technologies.

6. Conclusion

This study explored the factors influencing teachers' intention to use an AI teaching support tool specifically Microsoft Copilot by integrating components from the TAM model, TPK competency framework, and Social Cognitive Theory (SCT). Based on survey data from 280 teachers, the results showed that most of the hypothesized relationships in the model were confirmed. Perceived ease of use (PEOU) and self-efficacy (SE) were the two factors that had the strongest influence on behavioral intention (BI), suggesting the need to support teachers not only technically but also psychologically when approaching new technology. However, some relationships did not reach statistical significance. Perceived usefulness (PU) did not affect self-efficacy, and more surprisingly, it had a negative impact on intention to use. These results need to be further tested in more in-depth studies, especially in real-world school contexts. Factors, such as experience with AI, organizational support or trust in technology may mediate these unclear relationships. Therefore, future studies with larger sample sizes and longitudinal designs will help to clarify the mechanisms underlying teachers' AI adoption behavior.

References

Adetayo, A. J., Aborisade, M. O., & Sanni, B. A. (2024). Microsoft copilot and anthropic claude AI in education and library service. *Library Hi Tech News*. https://doi.org/10.1108/LHTN-01-2024-0002

Ali, O., Murray, P. A., Momin, M., Dwivedi, Y. K., & Malik, T. (2024). The effects of artificial intelligence applications in educational settings: Challenges and strategies. *Technological Forecasting and Social Change*, *199*, 123076. https://doi.org/10.1016/j.techfore.2023.123076

Bandura, A. (2023). *Social cognitive theory: An agentic perspective on human nature*: Hoboken, NJ: John Wiley & Sons.

Chuyen, N. T. H. (2023). An empirical analysis of predictors of AI-powered design tool adoption. *TEM Journal*, *12*(3), 1482-1489.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319-340. https://doi.org/10.2307/249008

Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. *In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)* (pp. 4171–4186). Association for Computational Linguistics. https://doi.org/10.18653/v1/N19-1423

Hazzan-Bishara, A., Kol, O., & Levy, S. (2025). The factors affecting teachers' adoption of AI technologies: A unified model of external and internal determinants. *Education and Information Technologies*, *30*(11), 15043–15069. https://doi.org/10.1007/s10639-025-13393-z

Hwang, H., Cho, G., Jung, K., Falk, C. F., Flake, J. K., Jin, M. J., & Lee, S. H. (2021). An approach to structural equation modeling with both factors and components: Integrated generalized structured component analysis. *Psychological Methods*, *26*(3), 273-294. https://doi.org/10.1037/met0000336

Joseph, F., Barry, J. B., Rolph, E. A., & Rolph, E. A. (2010). *Multivariate data analysis*. Upper Saddle River, NJ: Pearson Prentice Hall.

Kim, K., & Kwon, K. (2023). Exploring the AI competencies of elementary school teachers in South Korea. *Computers and Education: Artificial Intelligence*, *4*, 100137. https://doi.org/10.1016/j.caeai.2023.100137

Kline, R. B. (2023). *Principles and practice of structural equation modeling*. New York: Guilford Publications.

Mardia, K. V., Kent, J. T., & Taylor, C. C. (2024). *Multivariate analysis* (Vol. 88). Hoboken, NJ: John Wiley & Sons.

Mishra, P., & Koehler, M. J. (2006). Technological pedagogical content knowledge: A framework for teacher knowledge. *Teachers College Record*, *108*(6), 1017-1054. https://doi.org/10.1111/j.1467-9620.2006.00684.x

Mishra, P., Warr, M., & Islam, R. (2023). TPACK in the age of ChatGPT and generative AI. *Journal of Digital Learning in Teacher Education*, *39*(4), 235-251. https://doi.org/10.1080/21532974.2023.2247480

Nazaretsky, T., Mejia-Domenzain, P., Swamy, V., Frej, J., & Käser, T. (2025). The critical role of trust in adopting AI-powered educational technology for learning: An instrument for measuring student perceptions. *Computers and Education: Artificial Intelligence*, *8*, 100368. https://doi.org/10.1016/j.caeai.2025.100368

Nemorin, S., Vlachidis, A., Ayerakwa, H. M., & Andriotis, P. (2023). AI hyped? A horizon scan of discourse on artificial intelligence in education (AIED) and development. *Learning, Media and Technology*, *48*(1), 38-51. https://doi.org/10.1080/17439884.2022.2095568

Nikolic, S., Wentworth, I., Sheridan, L., Moss, S., Duursma, E., Jones, R. A., . . . Middleton, R. (2024). A systematic literature review of attitudes, intentions and behaviours of teaching academics pertaining to AI and generative AI (GenAI) in higher education: An analysis of GenAI adoption using the UTAUT framework. *Australasian Journal of Educational Technology*, *40*(6), 56–75. https://doi.org/10.14742/ajet.9643

Ouyang, F., & Jiao, P. (2021). Artificial intelligence in education: The three paradigms. *Computers and Education: Artificial Intelligence*, *2*, 100020. https://doi.org/10.1016/j.caeai.2021.100020

Stratton, J. (2024). An introduction to microsoft copilot. In copilot for microsoft 365: Inside copilot. Apress, Berkeley, CA. https://doi.org/10.1007/979-8-8688-0447-2_2

Sumandal, A. H. (2023). Teachers' self-efficacy with artificial intelligence (AI) based educational tools. *Ignatian International Journal for Multidisciplinary Research*, *1*(1), 1-10. https://doi.org/10.17613/fpyer-ek397

Tschannen-Moran, M., & Hoy, A. W. (2001). Teacher efficacy: Capturing an elusive construct. *Teaching and Teacher Education*, *17*(7), 783-805. https://doi.org/10.1016/S0742-051X(01)00036-1

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425-478. https://doi.org/10.2307/30036540

Vinh, N.-T., Phung, T.-N., & Cuong, D.-D. (2024). A bibliometric and thematic analysis of systematic reviews of artificial intelligence in education. In P. T. Nghia, V. D. Thai, N. T. Thuy, L. H. Son, & V.-N. Huynh (Eds.), *ICTA 2023* (Vol. 848, pp. 337-351). Cham: Springer.

Walter, Y. (2024). Embracing the future of artificial intelligence in the classroom: The relevance of AI literacy, prompt engineering, and critical thinking in modern education. *International Journal of Educational Technology in Higher Education*, *21*(1), 15. https://doi.org/10.1186/s41239-024-00448-3

Wang, F., King, R. B., Chai, C. S., & Zhou, Y. (2023). University students' intentions to learn artificial intelligence: The roles of supportive environments and expectancy–value beliefs. *International Journal of Educational Technology in Higher Education*, *20*(1), 51. https://doi.org/10.1186/s41239-023-00417-2

Wang, H., Li, J., Wu, H., Hovy, E., & Sun, Y. (2023). Pre-trained language models and their applications. *Engineering*, *25*, 51-65. https://doi.org/10.1016/j.eng.2022.04.024

Wang, S., Xu, T., Li, H., Zhang, C., Liang, J., Tang, J., . . . Wen, Q. (2024). Large language models for education: A survey and outlook. *arXiv preprint arXiv:2403.18105*.

Xu, S., Chen, P., & Zhang, G. (2024). Exploring Chinese university educators' acceptance and Intention to use AI tools: An application of the UTAUT2 model. *Sage Open*, *14*(4), 1-13. https://doi.org/10.1177/21582440241290013

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education–where are the educators? *International Journal of Educational Technology in Higher Education*, *16*(1), 1-27. https://doi.org/10.1186/s41239-019-0171-0

Zha, H., Li, W., Wang, W., & Xiao, J. (2025). The paradox of AI empowerment in primary school physical education: Why technology May Hinder, not help, teaching efficiency. *Behavioral Sciences*, *15*(2), 240. https://doi.org/10.3390/bs15020240