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An Empirical Analysis of Predictors of AI-Powered Design Tool Adoption

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***Abstract* – This study examined the relationships among the dimensions of Unified Theory of Acceptance and Use of Technology (UTAUT) and external variables in the context of using artificial intelligence (AI)-powered tools for lecture design. After four months of utilizing the tools, 208 participants took the survey via Google Form. The structural equation model was utilized to analyze the obtained responses. Findings showed that performance expectancy, effort expectancy, social influence, and availability/accessibility are reliable predictors of users' intentions to utilize AI-powered design tools. However, the effects of facilitating conditions and trust and confidence are insignificant. The proposed conceptual model accounted for 54.6% of the data variation. This study provides designers and developers of AI-powered design tools with theoretical and practical implications that can enhance the practical adoption and utilization of these tools.**

***Keywords* – SEM, AI-powered design tools, UTAUT, factor analysis, empirical analysis.**

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1. Introduction

There has been an increasing desire in investigating the potential of emerging technologies, such as AI-powered tools, to enhance the quality of education over the past few years [1],[2],[3].

One area where such technologies could have a significant impact is in creating engaging and effective learning materials for primary school students. Studies have shown that students learn faster from pictures than text-only and that visual aids can enhance student engagement and understanding of complex concepts [4], [5]. However, primary school teachers often lack the technical skills and resources [6], [7] to create high-quality images that effectively convey information from text-based materials. The traditional approach to creating teaching materials involves manual design, which can be time-consuming and requires specialized technical skills [8], [9]. Moreover, many primary school teachers lack the necessary training and experience to create visually appealing materials [10], [11]. As a result, lectures can often be unprofessional and fail to capture students' attention and interest. To address this issue, emerging technologies such as AI-powered design tools offer an efficient and effective way for primary school teachers to create engaging and visually appealing learning materials [12], [13]. These tools can automate the design process, allowing teachers to quickly generate high-quality images that are tailored to their students' needs [13], [14].

However, despite the potential benefits of using AI-powered design tools, research on understanding the facets that influence primary school teachers' intentions to adopt and use these tools in their professions is scarce. Therefore, the current study aims to investigate the intention to use AI-powered design tools among primary school teachers, with a particular focus on the dimensions that affect their adoption and utilization of these tools.

While there is some research on the use of technology in education [3], [15], [16], there is limited research specifically on the use of AI-powered design tools in primary school education. Additionally, there is a little available investigation on the determinants that affect primary school teachers' intentions to adopt and use these tools in their teaching practices. This research gap highlights the need for a comprehensive investigation into the dimensions influencing primary school teachers' intention to utilize AI-powered design tools. Specifically, the study aims to:

- Identify the factors affecting primary school teachers' intention to utilize AI-powered design tools.
- Investigate the relationships among the identified factors and primary school teachers' intention to utilize AI-powered design tools.

2. Literature Review

Various theoretical frameworks have been utilized to study the adoption and acceptance of technology. Among these frameworks, models proposed by [17], [18] are some of the commonly employed. The TAM paradigm has been extensively utilized in understanding technological acceptance, wherein it emphasizes the importance of efficiency and its simplicity [19]. Although the model has been applied in various domains such as healthcare and business, it has limitations, particularly in accounting for social and contextual factors that may impact technology acceptance [17]. On the other hand, TRA emphasizes attitudes and subjective norms in predicting behavior. It posits that attitudes and social pressures to engage in a behavior affect users' intention, and this intention then impacts their true behaviour [17]. The TPB, building upon TRA, includes the perceived behavioral control construct, which posits that an individual's perception of their ability to control their behavior influences their intention to engage in that behavior and actual behavior. Venkatesh *et al.* proposed a comprehensive framework that integrates concepts from several theoretical frameworks, including TAM, TRA, and TPB[17]. It is made up of four core concepts: expected performance, expected effort, social influence, and supportive environments. UTAUT has been validated by various empirical studies in diverse settings, proving its effectiveness in explaining the factors influencing technology adoption. The choice of UTAUT in this study was based on its extensive coverage, simplicity, and suitability to the context of primary school education, as well as its ability to consider external factors that could affect technology acceptance and use.

By using UTAUT, the current research aims to explore the determinants influencing the intention to utilize AI-powered design tools among primary school teachers, specifically examining the impact of availability and accessibility and trust and confidence as external factors.

Availability and accessibility are important external determinants that can influence the motive for utilization of the technology [20], [21]. The availability of a technology refers to its physical presence and the ease with which it can be accessed, while accessibility refers to how simple it is to understand how to make use of technology. In the context of AI-powered design tools for primary school teachers, availability and accessibility could refer to the availability and accessibility of these tools in schools and the degree of ease required for teachers to acquire the necessary skills to operate these tools. The literature suggests that trust and confidence are important external factors that can predict the motivation to employ a technology [22], [23]. Trust refers to the belief that a technology will work as intended and that it is reliable and secure, while confidence refers to the belief that the user can use the technology effectively. In the context of AI-powered design tools for primary school teachers, trust and confidence could refer to the trust that teachers have in the accuracy and reliability of these tools and their confidence in their ability to use them effectively.

On the basis of the aforementioned studies, six hypotheses were developed as follows:

- Hypothesis 1: Primary school teachers' perceived usefulness of AI-powered design tools positively influences their intention to use these tools for creating engaging lectures.
- Hypothesis 2: Primary school teachers' perceived ease of use of AI-powered design tools positively influences their intention to use these tools for creating engaging lectures.
- Hypothesis 3: The extent to which primary school teachers perceive that other teachers or education authorities think they should use AI-powered design tools positively influences their intention to use these tools for creating engaging lectures.
- Hypothesis 4: The extent to which primary school teachers perceive that their organization and technical infrastructure support the use of AI-powered design tools positively influences their intention to use these tools for creating engaging lectures.

- Hypothesis 5: The availability and accessibility of AI-powered design tools positively influence primary school teachers' intention to use these tools for creating engaging lectures.
- Hypothesis 6: The level of trust and confidence that primary school teachers have in the accuracy and effectiveness of AI-powered design tools positively influences their intention to use these tools for creating engaging lectures.

3. Methodology

This section outlines the approach, procedures, and techniques utilized to achieve the research objectives. In this study, the methodology section is divided into three sub-sections: Research Design, Samples and Data Gathering Tool, and Data Analysis. Each sub-section contributes to the overall methodological framework and ensures the reliability and validity of the research findings.

3.1. Research Design

This investigation engaged quantitative research methodology to explore the determinants of primary school teachers' satisfaction in utilizing AI-powered design tools. To enhance the teachers' skills, the authors conducted a training program on how to use AI-powered design tools to develop lectures, which were delivered via face-to-face sessions, online channels, and pre-recorded videos. To ensure the suitability of the tools [13], [14], [24] for the participants, the authors selected Microsoft Power Point Designer [25] and Microsoft Image Creator that were easily accessible and familiar to the participants. The training was carried out between January and March 2023, and a survey was planned to be administered to the participants in April 2023, following the end of the training program. This methodology is consistent with the recommended best practices in the literature for evaluating the effectiveness of professional development programs and assessing teacher satisfaction. The survey was completed by April 2023.

3.2. Samples and Data Gathering Tool

The current investigation examines northern highland Vietnamese elementary school teachers, with approximately 500 potential participants teaching in the provinces of Bac Giang, Lang Son, Thai Nguyen, Lao Cai, and Son La. Study participants were chosen using a non-random technique from the accessible population.

To ensure confidentiality and obtain informed consent, an online survey was conducted using Google Form. Participants were informed of the study's purpose, data type, storage, distribution, and their ability to opt-out at any time. The survey was conducted over a two-week period, and the questionnaire included two sections. The former collected background data, while the latter contained 21 questions that measured the level of intention with AI-powered design tools using the Likert scale. The survey questions were repurposed from those used in other studies [17], [22], [23] and modified to fit the context of this study. Before distribution, two experts in the field reviewed the questions for reliability and face validity. The researchers used list-wise deletion to exclude records with missing or abnormal data.

After collecting the data, the study excluded responses that were not appropriate, such as those with only one option selected (n=115) and missing values (n=83). Thus, the final sample size for analysis was 208, which accounted for 51.23% of the total responses received (n=406). Determining the appropriate sample size for a study is a debated issue in the literature, with varying recommendations from different scholars. For example, Kock and Hadaya [26] suggested a minimum sample size of 100-200 subjects, while Anderson and Gerbing [27] argued that a sample size of 100 is adequate for convergence, and 150 samples would be enough for both convergence and accuracy when dealing with factors with three or more indicators. The number of participants in this investigation was calculated using a method proposed by Kline [28], which suggested a minimum participant of 200. Since the actual participants in the current study exceeded the recommended threshold of 200, the study met its sample size requirements.

Table 1 presents the general profiles of respondents. Among primary school teachers, 37% were male and 63% were female. The age distribution of the participants was as follows: 14% of participants were between the ages of 18 and 25 years, 35% were between 26 and 35, 33% were between the ages of 36 and 45, and 18% were older than 45. The majority of respondents had an undergraduate degree (54%), followed by those with vocational training (22%) and graduate degrees (25%). With respect to experience, the highest percentage of primary school teachers had less than five years of expertise (36%), then those with five to ten years of professions (31%), 11-20 years of practices (21%), and over two decades expertise (13%). These demographic characteristics suggest that the study sample is diverse within the context of age, educational level, and professional background, which could enhance the external validity of the research.

Table 1. A Summary of properties of the primary school teachers

Property	Item	No	%
Gender	Male	77	37
	Female	131	63
Age	18 - 25	30	14
	26 - 35	72	35
	36 - 45	68	33
	Over 45	38	18
Level of Education	Vocational training	45	22
	Undergraduate	112	54
	Graduate	51	25
Year of Experience	< 5	74	36
	5-10	64	31
	11-20	43	21
	>20	27	13
Total		208	100

3.3. Data analysis

To assess the proposed research model, the study will utilize Generalized Structured Component Analysis (GSCA) method [29]. GSCA is a variance-based Structural Equation Modeling method which is capable of evaluating reflective and formative latent variables. It can analyze intricate models that include various kinds of latent variables and has been applied to diverse fields. GSCA can handle complex models with multiple dependent variables by modeling both formative and reflective latent variables, which leads to a more comprehensive analysis of the relationships between different constructs. Additionally, GSCA is particularly useful in situations where traditional SEM techniques are not applicable, such as when the data violates assumptions of normality or sample sizes are small [29]. GSCA utilizes robust estimation methods to account for these issues, making it a flexible and powerful tool for analyzing complex datasets. The GSCA output provides estimates of the model parameters, including factor loadings, path coefficients, and error variances, which can be used to test hypotheses regarding the relationships between observed and latent variables.

4. Results

The construct quality measures for six different constructs are provided in Table 2, which includes UTAUT's factors in conjunction with external dimensions as Availability/Accessibility (AA), Trust and Confidence (TC). The average variance extracted (AVE) metric compares measurement bias to concept variation. All constructs have AVE scores greater than .5 [28], indicating their reliability. The second measure is alpha, which measures internal consistency reliability. The alpha ratings for every single construct are over .7 [28], indicating good internal consistency reliability. The third measure is rho, which measures composite reliability. All constructs have rho scores greater than .8 [28], indicating good composite reliability. Overall, the construct quality measures suggest that the six constructs are reliable and internally consistent measures of the underlying latent variables they represent. These measures are consistent with the guidelines of Joseph F. Hair Jr. *et al.* [30] and Kline [28].

Table 2. Construct quality measures

	PE	EE	SI	FC	AA	TC	BI
AVE	.572	.622	.654	.583	.611	.644	.588
Alpha	.821	.784	.756	.792	.765	.738	.712
Rho	.837	.855	.912	.845	.849	.828	.837

Table 3 displays the estimates of the loadings for different constructs, including UTAUT' factors, Availability/Accessibility (AA), Trust/Confidence (TC), and Behavioral Intention (BI). The estimates for PE constructs range from .715 to .843, with standard errors (SE) ranging from .033 to .079. The 95% confidence intervals (CI) for PE constructs range from .521 to .824. The EE constructs have higher estimates, ranging from .832 to .933, with relatively lower SEs ranging from .013 to .029 and wider 95% CI ranges from .768 to .953. The estimates for SI constructs lie between .81 and .951, with SE between .012 and .036, and 95% CIs lie between .715 and .969. The FC constructs have similar estimates of .855 to .87, with SEs of .03 to .039 and 95% CIs of .783 to .923. The AA constructs have estimates ranging from .853 to .864, with SEs lie between .022 and .042, and 95% CIs of .711 to .898. The TC constructs have estimates ranging from .866 to .9, with SE spanning from .017 to .025, and 95% CIs are within .832 and .931. Finally, the BI constructs have estimates ranging from .794 to .88, with SE between .024 and .035 and 95% CIs lie between .719 and .926.

These loadings are essential in developing a comprehensive understanding of the relationships between different constructs in the study.

Table 3. Estimate of loadings

	Estimate	SE	95%CI	
Performance Expectancy (PE)				
PE1	.715	.079	.521	.824
PE2	.758	.055	.631	.872
PE3	.844	.033	.781	.898
Effort Expectancy (EE)				
EE1	.933	.013	.905	.953
EE2	.832	.027	.779	.886
EE3	.837	.029	.768	.88
Social Influence (SI)				
SI1	.951	.012	.925	.969
SI2	.81	.036	.715	.864
SI3	.915	.023	.863	.95
Facilitating Conditions (FC)				
FC1	.87	.03	.81	.923
FC2	.855	.039	.783	.914
FC3	.87	.03	.81	.923
Availability and accessibility (AA)				
AA1	.862	.022	.82	.896
AA2	.864	.025	.804	.898
AA3	.853	.042	.711	.921
Trust and Confidence (TC)				
TC1	.866	.025	.82	.922
TC2	.9	.017	.874	.931
TC3	.884	.021	.832	.915
Behavioral Intention (BI)				
BI1	.794	.035	.719	.851
BI2	.88	.024	.833	.926
BI3	.834	.033	.76	.883

The GSCA experiment yielded four fit measures, namely FIT, AFIT, GFI, and SRMR. The FIT and AFIT measures evaluate the model's absolute fit, while the GFI measures its relative fit, and the SRMR measures the variance between the measured and predicted correlations. The obtained FIT measure of 0.546 and the AFIT measure of 0.542 indicate that the model fits acceptably. The GFI measure of 0.934 suggests that the model's fit is good relative to the null model, which has no relationships among the variables. A GFI value exceeding 0.90 is typically considered acceptable. Finally, the SRMR measure of 0.072 demonstrates that the model fits well, with a value lower than 0.08 indicating acceptable fit.

Table 4. Path coefficients

	Estimate	SE	95%CI	
Performance Expectancy → Behavioral Intention	.523*	.068	.396	.644
Effort Expectancy → Behavioral Intention	.322*	.096	.117	.491
Social Influence → Behavioral Intention	.374*	.082	.212	.531
Facilitating Conditions → Behavioral Intention	.035	.096	-.114	.249
Availability/Accessibility → Behavioral Intention	.464*	.085	.281	.619
Trust and Confidence → Behavioral Intention	.16	.108	-.019	.35

* Statistically significant at .05 level

Table 4 presents the estimates, SE, and 95% CIs for the relationships between several constructs and behavioral intention. The standard error (SE) for each estimate indicates the precision of the estimate, while the 95% CI provides a spectrum of plausible outcomes for the true population variable. The asterisk (*) next to some estimates indicates that they are at the .05 threshold of significance, implying that the relationships they represent are unlikely to have arisen by chance. The outcomes indicate that performance expectancy has the highest positive relationship with behavioral intention, yielding an estimate of .523, SE of .068, and 95% CI between .396 and .644. Similarly, there is a strong positive relationship between intentional behavior and both expectation of effort and the effect of society, with estimates of .322 and .374, respectively. The estimates for both constructs are at the .05 threshold of significance and the 95% CIs do not contain zero, indicating that they have a reliable relationship with behavioral intention.

On the other hand, there is no statistically significant relationship between facilitating conditions and intentions to behave, with an estimate of .035, SE of .096, and 95% CI between -.114 and .249. Trust and confidence also show a non-significant relationship with behavioral intention, with an estimate of .16, SE of .108, and 95% CI between -.019 and .35. Finally, there is a strong positive correlation between availability/accessibility and behavioral intention, with an estimate of 0.464, SE of 0.085, and 95% CI between 0.281 and 0.619. Overall, the results suggest that intentional behavior can be predicted in part by the individual's beliefs about the importance of outcome, effort, social influence, and accessibility.

5. Discussion

The purpose of this investigation was to examine the effects of constructs in the UTAUT model along with availability/accessibility (AA), trust/confidence (TC), and behavioral intention (BI) in utilizing AI-powered tools for designing lectures. There was a good fit between the data and the suggested conceptual model, with the model explaining 54.6% of the variation in behavioral intention.

The results demonstrate that performance expectancy (H1: $\beta = .523$), effort expectancy (H2: $\beta = .322$), social influence (H3: $\beta = .374$), and availability/accessibility (H5: $\beta = .464$) all have a positive and statistically significant effect on primary school teachers' intention to utilize AI-powered design tools at the .05 threshold of significance. These findings suggest that users are more likely to adopt AI-powered design tools when they believe that the tools are useful (performance expectancy), require little effort (effort expectancy), influenced by important people in their lives (social influence), and accessible (availability/accessibility).

On the other hand, the results show that facilitating conditions (H4: $\beta = .035$, $p > .05$), and trust/confidence (H6: $\beta = .16$, $p > .05$) do not have a strong relationship with behavioral intention to use AI-powered design tools. The non-significant results for these two factors suggest that users' intention to use AI-powered design tools is not significantly dependent on the number of resources available (facilitating conditions) or the level of trust and confidence in the tools. There could be several reasons why facilitating conditions and trust/confidence were not the predictors of behavioral intention to adopt AI-powered design tools. Firstly, it is possible that the participants in the study already had access to sufficient resources and support, and thus, the availability of facilitating conditions did not affect their intention to adopt the AI-powered design tools significantly. Additionally, the lack of a significant effect of trust and confidence may suggest that users did not view trust and confidence as a critical factor in their decision to use AI-powered design tools. Alternatively, users may have had concerns about the accuracy, reliability, or ethical implications of using AI-powered design tools, which could have affected their level of trust and confidence in the tools. Moreover, it is also possible that the study lacked statistical power to detect a significant effect of these two factors on behavioral intention. This may be due to the sample size or measurement limitations of the study. Further research with a larger sample size and more comprehensive measurement of facilitating conditions and trust and confidence may help to provide more conclusive results.

In comparison with previous studies, these findings are generally consistent with previous research on the factors influencing users' intention to utilize technology. For instance, prior studies on technology adoption have supported the proposition that realistic expectations of both performance and effort have a favorable impact on future behaviors, such as the TAM model. Similarly, both theories of reason action and planned behavior corroborate the idea that social influence has a positive impact on behavior in the future. However, the non-significant effect of facilitating conditions and trust and confidence on behavioral intention is inconsistent with some previous studies that have found these factors to be significant predictors of technology acceptance.

The research has important theoretical implications for the study of how primary school teachers accept and use new technologies. The findings confirm the significance of the UTAUT model in understanding users' behavioral intentions towards AI-powered design tools. The study also shows that the factors affecting users' intention to use AI-powered design tools are like those identified in previous studies on technology acceptance. However, the study highlights the importance of considering the unique characteristics of AI-powered design tools, such as their complexity and potential impact on design outcomes, when investigating factors influencing their adoption. The practical implications of this study are relevant to both designers and developers of AI-powered design tools. First, the study provides insights into the factors that can positively affect users' intention to adopt these tools, such as the expectation of performance and effort, the influence of colleagues, and availability/accessibility of resources. Therefore, designers and developers should focus on improving the usability and ease of use of these tools, while also highlighting their potential benefits and the support they can provide in the design process. Second, the study highlights the importance of addressing users' concerns about the potential negative consequences of using AI-powered design tools, such as job displacement or loss of creativity. Designers and developers should take steps to mitigate these concerns and demonstrate the complementary role of AI-powered design tools in the design process. Finally, the study suggests that providing users with the necessary resources and support to use AI-powered design tools may not be sufficient to increase their adoption. Building trust and confidence in these tools is also crucial, and this can be achieved through transparency about how the tools work, their limitations, and their potential impact on design outcomes.

6. Conclusion

In conclusion, the current research aimed to investigate the determinants influencing the intention to utilize AI-powered design tools. Based on the analysis of the collected data, the findings suggest that the expectation of performance and effort, the influence of colleagues, and availability/accessibility of resources have a statistically significant effect on primary school teacher's intention to adopt AI-powered design tools. However, facilitating conditions, trust and confidence are not reliable predictors of participants' intention to practice these tools. The findings of current research have important theoretical and practical implications. Theoretically, this study provides a better understanding of the factors that predict teachers' intention to utilize AI-powered design tools. This knowledge can be used to develop and refine theories and models of technology adoption and use. Practically, the findings can help designers and developers of AI-powered design tools to understand the factors that are important to users and to develop more effective strategies for promoting the adoption and use of these tools.

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