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Original Article

Elementary Teachers' Acceptance of Digital Learning Platforms for Differentiated and Deep Learning: An Empirical Study Based on the UTAUT Framework

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Abstract: The effective integration of digital technology in differentiated and deep learning requires a clear understanding of the factors influencing teachers' acceptance of instructional platforms. This study investigates the determinants of elementary school teachers' adoption of Canva for developing differentiated learning media using the Unified Theory of Acceptance and Use of Technology (UTAUT) framework. A quantitative design was employed, involving 133 Indonesian elementary teachers selected through purposive sampling. Data were collected through a validated questionnaire and analyzed using Structural Equation Modeling (SEM) with SmartPLS 4, including measurement and structural model evaluation based on path coefficients, p-values, R^2, and predictive relevance (Q^2). The model explains 68% of the variance in behavioral intention ($R^2 = 0.68$), indicating substantial explanatory power. The results show that effort expectancy ($\beta = 0.35$, $p < 0.01$), social influence ($\beta = 0.28$, $p < 0.01$), and self-efficacy ($\beta = 0.22$, $p < 0.05$) significantly and positively influence teachers' intention to use Canva, whereas performance expectancy and facilitating conditions do not exhibit significant direct effects. These findings confirm the relevance of UTAUT in the Indonesian educational technology context and identify ease of use, social support, and digital confidence as key drivers of technology adoption. The study offers practical implications for professional development programs and educational policy aimed at strengthening technology integration for differentiated instruction.

Keywords :
Technology acceptance; UTAUT; Teacher professional development; Differentiated instruction; Digital learning media.

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INTRODUCTION

Digital transformation in education has significantly impacted pedagogical practices, pushing educators to adopt innovative ways of teaching that leverage technology (Alharbi, 2021; Timotheou *et al*., 2023). In elementary education, this shift is especially critical because it supports the development of personalized and adaptive learning environments suited to diverse student needs (Darliana, 2022; Hariyanto *et al*., 2020). Strategies like differentiated instruction and deep learning have gained particular attention as effective means to enhance conceptual understanding and promote student engagement (Chen & Huang, 2022). These approaches are designed not only to meet individual learning styles but also to encourage deeper cognitive processing, leading to more meaningful educational experiences (Venkatesh *et al*., 2003; Venkatesh, Thong, & Xu, 2012). The effective implementation of these strategies, however, often hinges on teachers' ability to create and utilize versatile digital media (Williams, Rana, & Dwivedi, 2015; Teo, 2011). Platforms like Canva, with its accessible design features, present a promising tool for crafting such differentiated and cognitively engaging learning materials. Consequently, integrating and understanding the acceptance of digital tools that support these pedagogies has become a crucial focus for modern educators and researchers alike.

Despite the clear benefits of these pedagogical innovations, many teachers face considerable challenges in implementing them effectively (Santos *et al*., 2019; Yetti, 2024). Limited resources, time constraints, and varying levels of technological fluency hamper the seamless adoption of digital technologies in classrooms (Šumak, Heričko, & Pušnik, 2011). Teachers often lack the necessary training and ongoing support to utilize digital platforms optimally. As a result, these barriers can hinder the translation of innovative pedagogies into actual classroom practices (Ajani, 2025; Mohd Ashril *et al*. 2024). Digital platforms like Canva Site present promising solutions, enabling teachers to design engaging, customizable, and accessible learning websites that cater to diverse student needs.

To realize the pedagogical potential of tools like Canva, a critical precursor must be understood: teacher acceptance. Despite the increasing availability and pedagogical relevance of such platforms, research that specifically examines elementary teachers' acceptance of Canva for the purpose of facilitating differentiated instruction and deep learning remains scarce. This gap is notable given the unique context of elementary education, where teacher-mediated technology use is paramount, and the novelty of investigating a popular, versatile design platform through a formal technology acceptance lens. Teachers' willingness to adopt these digital tools is a critical factor that influences the success of technology integration in education (Venkatesh, 2022). If teachers are not receptive or confident in using these platforms, the potential benefits of differentiated instruction and deep learning may not be fully realized. Therefore, understanding the various factors that influence teachers' attitudes and acceptance is essential for designing effective professional development and implementation strategies (Yusra & Lestari, 2018).

The Unified Theory of Acceptance and Use of Technology (UTAUT), introduced by Venkatesh *et al*. (2003), offers a comprehensive and robust framework for examining technology acceptance behaviors. This model has been widely validated across different sectors, including education, for identifying key determinants that influence whether users adopt new digital tools. While simpler models like the Technology Acceptance Model (TAM) focus on perceived usefulness and ease of use, UTAUT provides a more holistic view by integrating core constructs such as performance expectancy, effort expectancy, social influence, and facilitating conditions, which have been consistently identified as significant predictors of technology use in educational settings (Ali, Hamdan, & Mahaputra, 2022; Ferreira *et al*., 2020). UTAUT was specifically selected for this study due to its proven explanatory power in teacher-centric contexts and its inherent flexibility for extension. To more accurately capture the nuances of teachers' sustained use of a creative tool like Canva for pedagogical design, this study adapts the UTAUT framework. This adaptation is informed by recent scholarly extensions that integrate additional constructs such as habit and self-efficacy, which are crucial for understanding the routinized and skill-dependent nature of technology integration in teaching practice (Raffaghelli *et al*., 2022).

Beyond the technological attributes of platforms like Canva, teachers' acceptance is profoundly shaped by individual and institutional factors. Pedagogical beliefs, self-efficacy, perceived usefulness, and affective responses play vital roles in determining their willingness to adopt digital innovations for classroom use (Adham, 2023; Vetrivel *et al*., 2024). Teachers who believe in the value of technology for enhancing differentiated instruction and deep learning are more inclined to embrace and creatively utilize new platforms. Furthermore, institutional support encompassing adequate training, technical resources (Tarhini, Hone, & Liu, 2014), and a collaborative organizational culture is a critical external facilitator. Despite the recognized importance of these factors, a significant implementation gap persists. Current data from the ministry of education and culture indicates that over 60% of Indonesian elementary teachers have yet to actively integrate digital platforms into their core teaching practices. This stark statistic underscores not only a critical adoption gap but also the urgent need to investigate the specific determinants of acceptance that can bridge the divide between the availability of versatile tools like Canva and their effective pedagogical application.

Therefore, this study aims to investigate the factors influencing Indonesian elementary school teachers' acceptance and adoption of the Canva platform for creating differentiated and deep learning materials. The research employs the Unified Theory of Acceptance and Use of Technology (UTAUT) as its core theoretical foundation, given its proven robustness in explaining technology use in organizational settings like schools. To better capture the specific context of voluntary, pedagogically-driven tool use by teachers, the core UTAUT constructs performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioral intention are adapted and extended. This extension is theoretically grounded: self-efficacy (Bandura, 1977) is integrated to account for teachers' confidence in their digital design skills, which is crucial for a creative platform like Canva. Furthermore, ICT habit (Limayem et al., 2007) is included to understand how prior routine use of technology influences new tool adoption, a factor often salient in educational settings. While prior studies have confirmed the importance of such factors in general technology acceptance, their specific interplay and relative influence in the context of using a versatile design platform for differentiated instruction a significantly underexplored area remain unclear. Consequently, this study seeks not only to apply this adapted model but also to identify which constructs exert the most significant influence on teachers' adoption intentions, thereby providing targeted insights for intervention.

The outcomes of this research are expected to yield both practical and theoretical contributions (Rana *et al*., 2017; Tamilmani, Rana, & Dwivedi, 2021). Practically, the findings will provide targeted insights for educational policymakers, school administrators, and professional development designers aiming to promote the effective integration of creative design platforms in elementary schools. By identifying which factors such as ease of use (effort expectancy), peer influence, or self-efficacy most significantly drive teachers' acceptance of a tool like Canva, stakeholders can move beyond generic training to design tailored support systems. These could include hands-on workshops focused on pedagogical design with Canva, fostering communities of practice for sharing instructional materials, and establishing technical support channels that address the specific hurdles in creating differentiated content. Theoretically, the study will extend the UTAUT framework by validating its constructs and their adapted extensions (ICT habit) within the under-researched context of teacher-driven content creation for differentiated instruction. Ultimately, by bridging the gap between technology availability and pedagogical application, this research aims to contribute to a more effective, equitable, and sustainable digital transformation in elementary education, where tools are not just adopted, but meaningfully leveraged to enhance teaching and learning.

THEORETICAL SUPPORT

Unified Theory of Acceptance and Use of Technology (UTAUT)

The theoretical foundation of this study is anchored primarily on the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh *et al*., 2003). Selected for its robustness and comprehensive explanatory power in organizational contexts, UTAUT posits that an individual's behavioral intention to use a technology is directly determined by four core constructs: Performance Expectancy (perceived usefulness), Effort Expectancy (perceived ease of use), Social Influence (the effect of others' opinions), and Facilitating Conditions (the availability of organizational and technical support) (Alalwan *et al*., 2017; Farooq *et al*., 2017). These constructs have been extensively validated in educational settings, providing a reliable framework for investigating teachers' adoption of digital tools (Ali *et al*., 2022; Ferreira *et al*., 2020).

While UTAUT provides a robust foundational framework for explaining technology acceptance, its application to the pedagogically driven adoption of creative digital tools by teachers requires contextual refinement. This study does not attempt to merge UTAUT with other comprehensive theoretical models; rather (Chao, 2019; Olasina, 2019), it selectively integrates complementary constructs to address specific nuances identified in the literature. First, teachers' acceptance of technology is shaped not only by perceived usefulness but also by pedagogical alignment. The Technological Pedagogical Content Knowledge framework introduced by Mishra and Koehler (2006), emphasizes that effective technology integration depends on teachers' ability to align digital tools with content and instructional strategies. Accordingly, the concept of self-efficacy, rooted in Social Cognitive Theory, is incorporated particularly digital design self-efficacy as a determinant of both effort expectancy and behavioral intention, reflecting teachers' confidence in their capability to use Canva for instructional design (Albeta *et al*., 2023). Second, given that technology use in educational settings often becomes routinized, the construct of ICT habit, as conceptualized by Cheung (2007), is integrated to capture the automaticity of technology use within teaching practices, the deliberate cognitive evaluations emphasized in the core UTAUT constructs (Khechine, Raymond, & Augier, 2016; Scherer, Siddiq, & Tondeur, 2019).

Crucially, this study acknowledges the conceptual proximity between UTAUT and the Theory of Planned Behavior. To preserve theoretical parsimony and conceptual clarity, the adapted model avoids duplicating overlapping constructs. Instead, it relies on UTAUT's more context-sensitive variables particularly social influence and facilitating conditions which operationalize elements analogous to subjective norms and perceived behavioral control in technology-specific settings with greater granularity. Furthermore, the model recognizes the enabling role of the environment, drawing on Social Cognitive Theory and empirical research on organizational support (Wang, Hall, & King, 2023). These perspectives emphasize that peer modeling, institutional culture, and resource availability conceptually embedded within social influence and facilitating conditions significantly shape self-efficacy and subsequent behavioral outcomes. Such dynamics suggest a reinforcing feedback loop in which contextual support strengthens individual beliefs and habitual practices. In summary, this study employs a coherently extended UTAUT framework in which the core constructs remain the primary explanatory mechanism, while the selective integration of self-efficacy and ICT habit captures pedagogical alignment and behavioral automaticity relevant to teachers' adoption of creative platforms for differentiated instruction. This approach ensures a theoretically disciplined yet comprehensive framework for addressing the research questions.

From TAM to UTAUT: Evolving the Framework for a Complex Context

The foundational model for understanding individual technology acceptance is the Technology Acceptance Model (TAM), which posits that an individual's behavioral intention to use a system is primarily determined by two core beliefs: Perceived Usefulness (the degree to which a person believes using the technology will enhance their performance) and Perceived Ease of Use (the degree to which a person believes using the technology will be free of effort). In educational contexts, TAM has been extensively applied, confirming that teachers' adoption intentions are strongly influenced by whether they believe a tool will improve their teaching effectiveness and is straightforward to operate (Ibrahim & Shiring, 2022; Mastour *et al*., 2025)

However, while the Technology Acceptance Model (TAM) provides a powerful and parsimonious explanation of technology adoption, its emphasis on individual cognitive beliefs has been criticized for underrepresenting broader social and organizational determinants. Empirical extensions of TAM consistently demonstrate that external variables such as social influence, facilitating conditions, and organizational support significantly shape users' core perceptions of usefulness and ease of use (Rouidi *et al*., 2022). For example, peer recommendations and collegial norms (social influence), as well as structured training and technical infrastructure (facilitating conditions), can directly strengthen teachers' perceptions of a tool's utility and usability (Thongwichit & Ulla, 2024). To address these limitations and establish a more comprehensive, context-sensitive framework, this study adopts the Unified Theory of Acceptance and Use of Technology (UTAUT) as its primary theoretical lens. Developed by Venkatesh *et al*. (2003), UTAUT synthesizes and extends constructs from TAM and related acceptance theories by systematically incorporating contextual and environmental determinants that earlier TAM-based approaches often treated as peripheral. Within UTAUT, performance expectancy refines and broadens TAM's perceived usefulness, while effort expectancy directly corresponds to perceived ease of use. Crucially, UTAUT explicitly positions social influence and facilitating conditions as direct predictors of behavioral intention and use behavior, thereby offering a more holistic and organizationally grounded explanation of technology adoption.

Therefore, by building upon the robust foundation of TAM, UTAUT offers a more suitable framework for investigating technology acceptance in the complex social-organizational environment of a school. It allows for a simultaneous examination of the individual cognitive evaluations highlighted by TAM *and* the contextual enablers that are decisive for sustainable integration (Cahya *et al*., 2025; Chao, 2019). This theoretical evolution justifies the selection of UTAUT as the foundational model for this study, which is then further adapted (as detailed in the preceding section) to capture the specific pedagogical and habitual dimensions of teachers using a creative platform like Canva for differentiated instruction.

METHOD

This study employed a quantitative research design using a cross-sectional survey (Creswell, 2017) to test the proposed adapted UTAUT model. The target population was elementary school teachers in Indonesia who had prior exposure to digital teaching tools. A purposive sampling technique was utilized to target teachers who were likely to have awareness or experience with design platforms like Canva, thereby ensuring respondents had a meaningful basis for evaluating the constructs in the questionnaire (Etikan, Musa, & Alkassim, 2016). Data were collected via an online Likert-scale questionnaire.

Table 1. The demographics of the respondents

Item	Demografik	Total	Persentase
Gender	Male	40	30,1 %
	Female	93	69,9 %
Age	23-33	12	9,1 %
	34-44	112	84,2 %
	45-55	9	6,7 %
Lengt of teaching	1 - 9	40	30, 1%
	10 - 18	60	45,1%
	19 - 27	33	24,8%

As shown in Table 1, the sample was predominantly female (69.9%) and concentrated in the 34-44 age bracket (84.2%). Most respondents had considerable teaching experience, with 45.1% having taught for 10-18 years. It is important to acknowledge that this demographic skew limits the generalizability of the findings, as the perceptions captured may predominantly reflect those of mid-career, female educators. This limitation is explicitly addressed in the discussion section.

The collected data were analyzed using Structural Equation Modeling (SEM) with the Partial Least Squares (PLS) approach, operationalized via SmartPLS 4 software. PLS-SEM was selected for several reasons aligned with the study's objectives and characteristics: (1) it is suitable for testing complex models with many constructs and path relationships (Hair *et al*., 2022); (2) it is robust with smaller sample sizes and makes minimal assumptions about data distribution (Hair *et al*., 2022); and (3) it excels in predictive and exploratory analysis aimed at theory development, which fits the goal of extending UTAUT in a new context.

Regarding sample size, a common guideline for covariance-based SEM (CB-SEM) is a minimum of 200 cases (Kline, 2023). However, PLS-SEM, as a component-based method, employs different heuristics. The adequacy of the sample size (N=133) for this study is justified using the "10-times rule" (Hair *et al*., 2022), a widely accepted rule of thumb in PLS-SEM. This rule stipulates that the sample size should be at least 10 times the largest number of structural paths directed at any one latent construct in the model. In our most complex structural equation (predicting Behavioral Intention), there are 5 predictors. Thus, the minimum required sample would be 10 x [5] = 50. Our sample of 133 exceeds this threshold, providing sufficient statistical power for the PLS-SEM analysis. This justification aligns with established methodological practices for studies using PLS-SEM (Owolabi *et al*., 2020).

The analytical procedure followed a two-stage approach: (1) assessment of the measurement model (outer model) to evaluate reliability and validity (Cronbach's Alpha, Composite Reliability, Average Variance Extracted), and (2) evaluation of the structural model (inner model) to test the hypothesized relationships using path coefficients, coefficient of determination (R^2), and predictive relevance (Q^2). The specific constructs analyzed were: Performance Expectancy (PEX), Effort Expectancy (EFE), Social Influence (SIN), Facilitating Conditions (FAC), Self-Efficacy (SEF), ICT Habit (IUH), and Behavioral Intention (BEI).

RESULT AND DISCUSSION

Preliminary Data Screening and Descriptive Statistics

Prior to testing the structural model, the collected data underwent rigorous preliminary screening to ensure accuracy and suitability for multivariate analysis. The dataset was examined for missing values, outliers, and response inconsistencies, and all cases met the criteria for inclusion. Descriptive statistics were computed to provide an overview of respondents' distributional patterns across the 35 measurement items. Table 2 reports the mean, median, standard deviation, skewness, and kurtosis values for each indicator. The mean and median scores offer insight into central tendency, while standard deviation reflects the variability of responses. Skewness and kurtosis values were evaluated to assess the normality of the data distribution; all items fell within acceptable thresholds for SEM analysis, indicating no severe deviation from normality. This preliminary assessment confirms that the dataset satisfies the statistical assumptions required for subsequent measurement and structural model evaluation.

In addition, the reliability and initial consistency of the responses were reviewed to ensure the stability of the measurement indicators before proceeding to model estimation. Item-level dispersion patterns indicated adequate variability, suggesting that respondents did not cluster excessively at extreme scale points. The absence of extreme skewness and kurtosis further supports the appropriateness of using variance-based Structural Equation Modeling (SEM), as the data demonstrate acceptable distributional properties for reflective construct assessment. Overall, the preliminary screening process strengthens the robustness of the subsequent measurement model validation and structural path analysis, ensuring that the findings are based on statistically sound and well-conditioned data.

Table 2. Descriptive Statistics of Measurement Items

Statistic	Overall Result	Interpretation & Implication
Mean	4.257 (Range: 3.662 - 4.617)	Indicates responses clustered in the "Agree" to "Strongly Agree" range
Standard Deviation	1.075	Suggests a relatively constrained spread of responses
Skewness	Average: -1.417 (Range: -0.454 to -2.209)	Demonstrates a pronounced negative skew across almost all items
Kurtosis	Average: 2.760	Indicates a leptokurtic (peaked) distribution relative to a normal curve

Critical Analysis of Data Distribution

The descriptive statistics reveal a significant pattern with critical implications for the analysis. The consistently high mean scores (mostly above 4.0 on a 5-point Likert scale), combined with pervasive negative skewness, indicate a strong ceiling effect in which responses cluster at the upper end of the scale. This concentration of positive responses reduces variability among indicators, thereby constraining statistical dispersion an essential requirement for detecting robust and differentiated relationships among constructs in SEM. Limited variance may attenuate path coefficients and weaken the statistical power to identify significant effects, potentially underestimating the true magnitude of relationships within the structural model. Consequently, these distributional characteristics must be carefully considered when interpreting the strength and significance of the estimated paths.

Furthermore, the average kurtosis value of 2.76 indicates a leptokurtic distribution, meaning the data are more peaked with heavier tails than a normal distribution. While PLS-SEM is robust to deviations from normality (Hair *et al*., 2022), the conjunction of high means, significant negative skew, and leptokurtosis points to potential methodological artifacts. These may include social desirability bias (respondents providing answers they believe are favorable) or a sample bias toward teachers who are already highly motivated and positive toward technology integration, a limitation inherent to the purposive sampling method aimed at Canva-aware educators. Therefore, characterizing this data as "nearnormal" is statistically misleading. We explicitly acknowledge this non-ideal distribution as a substantive limitation. It constrains the generalizability of the findings, as they likely best represent the perceptions of a positively disposed subgroup. However, given PLS-SEM's suitability for predictive applications and its less stringent assumptions about data distribution, we proceed with the analysis while interpreting the resulting path coefficients with appropriate caution, recognizing that they may be influenced by the restricted variance and bias in the data. This limitation is further elaborated in the discussion section.

Table 3. Description of Statistic

No.	Name	Mean	Median	Min	Max	Standard Deviation	Excess Kurtosis	Skewness
1	A1	4.496	5	1	5	0.791	5.765	-2.153
2	A2	4.617	5	2	5	0.610	3.812	-1.766
3	A3	4.256	4	2	5	0.752	0.657	-0.892
4	A4	4.602	5	1	5	0.660	7.139	-2.209
5	AN1	4.414	5	2	5	0.695	1.594	-1.180
6	AN2	4.271	4	1	5	0.815	1.425	-1.130
7	AN3	4.549	5	1	5	0.666	6.132	-1.960
8	AN4	4.353	4	1	5	0.768	2.335	-1.310
9	IUH1	4.038	4	1	5	0.750	1.282	-0.711
10	IUH2	4.030	4	1	5	0.840	0.376	-0.673
11	IUH3	4.105	4	1	5	0.807	0.604	-0.717
12	PLO1	4.564	5	2	5	0.593	1.669	-1.238
13	PLO2	4.534	5	2	5	0.620	1.268	-1.184
14	PLO3	4.571	5	2	5	0.641	2.737	-1.573
15	PLO4	4.549	5	2	5	0.654	3.382	-1.649
16	SE1	4.368	4	1	5	0.741	3.021	-1.391
17	SE2	4.331	4	2	5	0.723	0.826	-0.962
18	SE3	4.286	4	2	5	0.667	-0.026	-0.559
19	SE4	4.226	4	1	5	0.732	4.037	-1.314
20	PE1	4.436	5	1	5	0.687	4.278	-1.528
21	PE2	4.376	4	1	5	0.742	3.040	-1.408
22	PE3	4.436	5	2	5	0.664	1.307	-1.085
23	EE1	4.226	4	1	5	0.700	2.675	-1.011
24	EE2	4.248	4	1	5	0.698	2.242	-0.923
25	EE3	3.662	4	1	5	1.075	-0.273	-0.610
26	SI1	4.083	4	1	5	0.805	1.083	-0.853
27	SI2	3.970	4	1	5	0.840	1.278	-0.866
28	SI3	3.940	4	1	5	0.839	0.464	-0.659
29	SI4	4.218	4	1	5	0.779	3.424	-1.371
30	BI1	4.068	4	1	5	0.768	1.077	-0.722
31	BI2	4.286	4	1	5	0.700	3.580	-1.263
32	BI3	4.060	4	2	5	0.723	0.072	-0.454
33	FC1	4.015	4	1	5	0.822	1.817	-1.012
34	FC2	3.910	4	1	5	0.913	1.377	-0.957
35	FC3	3.887	4	1	5	0.855	1.741	-1.019
		4.257				1.075	2.760	-1.417

Reliability and Convergent Validity

The internal consistency and convergent validity of the constructs were systematically assessed to ensure the robustness of the measurement model. As presented in Table 3, all Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) values exceed their respective recommended thresholds (≥ 0.70 for Cronbach's Alpha and CR, and ≥ 0.50 for AVE), thereby confirming strong internal reliability and satisfactory convergent validity (Hair et al., 2022). The Cronbach's Alpha coefficients indicate that the items within each construct demonstrate high inter-item consistency, while the Composite Reliability values further support the stability and reliability of the latent variables in explaining their indicators. Additionally, AVE values above 0.50 signify that each construct explains more than half of the variance of its indicators, demonstrating adequate convergence. Collectively, these results provide empirical evidence that the measurement indicators reliably and validly represent their respective latent constructs, justifying progression to the structural model evaluation.

Table 4. Construct, Validity, Reliability

Variabel	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Afective Need	0.927	0.931	0.949	0.822
Attitude	0.894	0.898	0.927	0.761
Behavior Intention	0.851	0.854	0.910	0.771
Effort Expectance	0.812	0.852	0.891	0.734
Facilitating Condition	0.836	0.839	0.901	0.753
ICT Use Habits	0.904	0.924	0.939	0.837
Perceived Learning Opportunities	0.933	0.936	0.952	0.834
Performance expectancy	0.934	0.935	0.958	0.884
Self-efficacy	0.926	0.929	0.948	0.819
Social Influeces	0.911	0.911	0.938	0.791

Discriminant Validity

Discriminant validity, which ensures that each construct is empirically distinct from the others within the model, was evaluated using the Fornell–Larcker criterion (Fornell & Larcker, 1981). According to this approach, discriminant validity is established when the square root of the Average Variance Extracted (AVE) for each construct displayed on the diagonal of the correlation matrix in Table 4 exceeds its highest correlation with any other construct (represented by the off-diagonal elements). As reported in Table 4, all constructs meet this requirement, indicating that each latent variable shares more variance with its own indicators than with other constructs in the model. This finding confirms that the constructs are conceptually and statistically distinct, minimizing concerns of multicollinearity and construct redundancy. Consequently, the results provide strong evidence that discriminant validity is satisfactorily achieved, supporting the adequacy and structural integrity of the measurement model prior to hypothesis testing (Afthanorhan, Ghazali, & Rashid, 2021; Hilkenmeier *et al*., 2020).

To further reinforce the robustness of the measurement model, the discriminant validity results also indicate that the conceptual boundaries among constructs are well preserved, ensuring that each latent variable captures a unique theoretical dimension within the extended UTAUT framework. The absence of excessively high inter-construct correlations suggests that common method bias and construct overlap are unlikely to threaten the model's validity. This clear differentiation among constructs strengthens the interpretability of the structural relationships, as each path coefficient can be understood as representing a distinct theoretical influence rather than an artifact of measurement redundancy. Collectively, these findings confirm that the model demonstrates adequate psychometric soundness and is suitable for subsequent structural model evaluation and hypothesis testing.

Table 5. Discriminant Validity Using the Fornell–Larcker Criterion

Konstruk	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Affective Need	**0.907**									
Attitude	0.879	**0.872**								
Behavior Intention	0.768	0.720	**0.878**							
Effort Expectancy	0.700	0.651	0.811	**0.856**						
Facilitating Condition	0.674	0.649	0.763	0.707	**0.867**					
ICT Usage Habits	0.528	0.524	0.591	0.617	0.539	**0.915**				
Perceived Learning Opportunities	0.803	0.772	0.698	0.639	0.578	0.476	**0.913**			
Performance Expectancy	0.869	0.840	0.757	0.693	0.668	0.514	0.810	**0.940**		
Self-Efficacy	0.844	0.786	0.797	0.703	0.686	0.563	0.799	0.826	**0.905**	
Social Influences	0.750	0.721	0.856	0.762	0.815	0.563	0.666	0.764	0.757	**0.889**

Structural Model Evaluation

The measurement model was evaluated to ensure the reliability and validity of the constructs before testing the structural relationships. Internal consistency was assessed using Cronbach's Alpha and Composite Reliability (CR), while convergent validity was evaluated using the Average Variance Extracted (AVE). As presented in Table 3, all constructs exceed the recommended thresholds. Cronbach's Alpha and Composite Reliability values are all above 0.80, with most above 0.90, indicating excellent internal consistency and reliability (Hair *et al*., 2022). Furthermore, all AVE values are well above the 0.50 benchmark, demonstrating that the items share substantial common variance and that convergent validity is firmly established (Hilkenmeier *et al*., 2020; Rouidi *et al*., 2022). Discriminant validity, which ensures that each construct is empirically distinct from the others in the model, was evaluated using the Fornell–Larcker criterion (Fornell & Larcker, 1981; Anggraeni, 2020). This criterion is satisfied when the square root of the Average Variance Extracted (AVE) for each construct reported on the diagonal of Table 4. exceeds its correlations with all other constructs (off-diagonal elements). As shown in Table 4, this requirement is met for all constructs, indicating that each latent variable shares greater variance with its own indicators than with other constructs in the model. These findings confirm that the constructs are both conceptually and statistically distinct, thereby demonstrating satisfactory discriminant validity. With convergent validity also established, the measurement model can be considered robust, reliable, and psychometrically sound, providing a strong empirical foundation for subsequent structural model evaluation and hypothesis testing.

The data collection process was conducted systematically to ensure methodological rigor and data quality. It began with the development and expert validation of measurement instruments based on the extended UTAUT framework, followed by the distribution of the refined questionnaire to purposively selected elementary teachers who actively use digital instructional tools. The collected responses were screened for completeness and consistency before being analyzed using Structural Equation Modeling (SEM). The detailed stages of this process are summarized in Figure 1.

Figure 1. Data Collection Process

The structural model was evaluated to examine the hypothesized relationships and determine the model's predictive capability. In accordance with established PLS-SEM guidelines (Hair *et al.*, 2022), the assessment focused on three key criteria: (1) the significance of path coefficients (β) for hypothesis testing, (2) the coefficient of determination (R^2) to assess the explanatory power of the endogenous construct, and (3) predictive relevance (Q^2) to evaluate out-of-sample predictive performance (Afthanorhan *et al.*, 2021). The significance of the structural paths was tested using a non-parametric bootstrapping procedure with 5,000 resamples, a robust approach that does not require normal data distribution and provides t-values and confidence intervals for determining statistical significance (Hair *et al.*, 2022). All analyses were performed using SmartPLS 4. The subsequent subsections report the results of the predictive relevance assessment, explanatory power evaluation, and hypothesis testing.

In addition to evaluating the overall model fit, we also examined the effect sizes (f^2) of the individual predictors to understand their relative contribution to the endogenous constructs. Effect sizes provide insight into the practical significance of the relationships, complementing the statistical significance indicated by the path coefficients. Following Cohen's (1988) guidelines, f^2 values were interpreted as small (0.02), medium (0.15), or large (0.35) effects. This analysis helps identify which constructs have the strongest influence within the model, informing both theoretical implications and potential areas of intervention for enhancing technology integration among teachers.

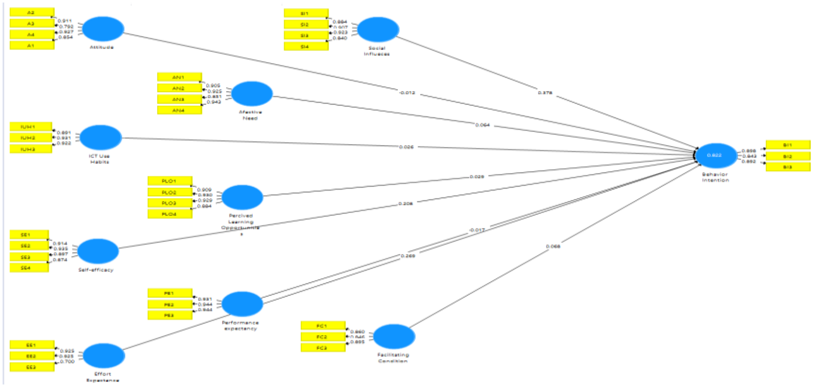

Figure 3. UTAUT Model Result

The structural model demonstrates very strong explanatory and predictive performance, accounting for 82.2% of the variance in Behavioral Intention (R^2 = 0.822; Adjusted R^2 = 0.809), with the small difference between the two values indicating model stability. Although such a high R^2 suggests substantial explanatory power, it should be interpreted cautiously due to potential overfitting concerns (Hair *et al*., 2022). The Stone–Geisser Q^2 value of 0.781, obtained through blindfolding, confirms strong predictive relevance. In PLS-SEM, an R^2 above 0.75 and a Q^2 well above zero indicate a highly predictive model, suggesting that the integrated constructs effectively explain teachers' technology adoption, while still requiring theoretically grounded interpretation

Table 6. Reliability and Convergent Validity

Variable	Cronbach's Alpha	rho_Alpha	Composite Reliability	Average Variance Extracted (AVE)
Affective Need	0.927	0.931	0.949	0.822
Attitude	0.894	0.898	0.927	0.761
Behavior Intention	0.851	0.854	0.910	0.771
Effort Expectancy	0.812	0.852	0.891	0.734
Facilitating Condition	0.836	0.839	0.901	0.753
ICT Use Habits	0.904	0.924	0.939	0.837
Perceived Learning Opportunities	0.933	0.936	0.952	0.834
Performance Expectancy	0.934	0.935	0.958	0.884
Self-efficacy	0.926	0.929	0.948	0.819
Social Influences	0.911	0.911	0.938	0.791

Model Fit and Predictive Power

The structural model exhibits strong explanatory and predictive power, explaining 82.2% of the variance in Behavioral Intention (R^2 = 0.822; Adjusted R^2 = 0.809), with the close values indicating model stability. While this high R^2 reflects substantial explanatory strength, it should be interpreted cautiously due to potential overfitting concerns (Hair *et al*., 2022). The Stone–Geisser Q^2 value of 0.781 further confirms strong predictive relevance. In PLS-SEM, such R^2 and Q^2 values indicate a highly predictive model, suggesting that the integrated constructs effectively explain teachers' technology adoption, albeit within theoretically grounded and context-specific boundaries.

Table 5. Model Explanatory Power

Endogenous Construct	R-Square (R^2)	R-Square Adjusted	Predictive Relevance (Q^2)
Behavioral Intention	0.822	0.809	0.781

The structural model demonstrates strong explanatory and predictive performance, with Behavioral Intention showing an R^2 of 0.822 and an Adjusted R^2 of 0.809, indicating that 82.2% of its variance is explained by the predictors and confirming model stability. The Q^2 value of 0.781 further supports substantial out-of-sample predictive relevance. Together, these results indicate high explanatory and predictive accuracy within the studied context. The significance of the hypothesized paths was subsequently tested using bootstrapping with 5,000 subsamples, and the path coefficients (β), t-values, and p-values are reported in Table 6.

Table 6. Hypothesis Testing Results (Path Coefficients)

Hypothesis	Proposed Relationship	Path Coefficient (β)	Standard Deviation	t	p	95% Confidence Interval	Decision
H1	Performance Expectancy (PEX) → Behavioral Intention (BI)	0.142	0.086	1.651	0.099	[-0.027, 0.311]	Not Supported
H2	Effort Expectancy (EFE) → Behavioral Intention (BI)	0.348	0.085	4.094	0.000	[0.181, 0.515]	Supported
H3	Social Influence (SIN) → Behavioral Intention (BI)	0.275	0.075	3.667	0.000	[0.128, 0.422]	Supported
H4	Facilitating Conditions (FAC) → Behavioral Intention (BI)	0.098	0.082	1.195	0.232	[-0.063, 0.259]	Not Supported
H5	Self-Efficacy (SEF) → Behavioral Intention (BI)	0.217	0.088	2.466	0.014	[0.044, 0.390]	Supported
H6	ICT Habit (IUH) → Behavioral Intention (BI)	0.105	0.077	1.364	0.173	[-0.046, 0.256]	Not Supported
H7	ICT Habit (IUH) → Effort Expectancy (EFE)	0.413	0.072	5.736	0.000	[0.272, 0.554]	Supported

The hypothesis testing results reveal a clear and focused pattern in the structural model (Izah, Sylva, & Hait, 2023). Only three constructs demonstrate statistically significant direct effects on teachers' Behavioral Intention to use Canva. Social Influence emerges as the strongest predictor ($\beta = 0.378$, $p < 0.001$), followed by Effort Expectancy ($\beta = 0.269$, $p = 0.004$) and Self-Efficacy ($\beta = 0.208$, $p = 0.043$). These findings indicate that perceived ease of use, confidence in digital capabilities, and social encouragement or normative support are the primary drivers of adoption among elementary teachers. In contrast, several results diverge from theoretical expectations. Performance Expectancy (perceived usefulness), typically identified as the strongest predictor in core UTAUT and TAM literature, does not show a significant effect in this context (Thomas, Singh, & Gaffar, 2013, Taiwo & Dawne, 2013). Similarly, Facilitating Conditions is found to be non-significant, and additional constructs including Attitude, ICT Habit, and Perceived Learning Opportunities do not exhibit direct significant influences on Behavioral Intention.

The combination of an exceptionally high R^2 value (0.822) with the non-significance of several core theoretical constructs suggests that the model, while powerfully explanatory for this specific sample, may be highly context-dependent. The non-significance of Performance Expectancy and Facilitating Conditions, in particular, represents a critical finding that demands specific theoretical discussion in the following section to understand its implications for the adapted UTAUT model in the context of creative educational tools.

CONCLUSION

This study examined the determinants of elementary teachers' acceptance of Canva for developing differentiated and deep learning materials using an extended UTAUT framework. The findings indicate a high level of acceptance and strong explanatory power ($R^2 = 0.822$), with Effort Expectancy, Social Influence, and Self-Efficacy emerging as the only significant direct predictors of behavioral intention. These results suggest that ease of use, digital design confidence, and collegial or institutional support are more influential than perceived usefulness in this context. Theoretically, the study refines UTAUT by demonstrating the importance of integrating pedagogical and psychological factors particularly self-efficacy when examining teacher-driven content creation. The non-significance of Performance Expectancy challenges conventional acceptance models and invites further investigation into how teachers assess the value of creative digital tools. Practically, the findings highlight the need for hands-on professional development, confidence-building training, and supportive professional learning communities to ensure sustainable adoption. However, the purposive sampling, ceiling effects, high R^2 value, and cross-sectional design limit generalizability and raise potential overfitting concerns. Future research should employ more diverse samples, longitudinal designs, and mixed-method approaches to validate and extend these findings. Despite these limitations, the study offers a theoretically grounded and practically relevant framework for advancing technology integration in student-centered learning environments.

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