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ORIGINAL RESEARCH

UNDERSTANDING THE FACTORS THAT INFLUENCE DIGITAL READINESS IN EDUCATION: A UTAUT STUDY AMONG DIGITAL TRAINING LEARNERS

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Abstract

Digital transformation is a critical element in modern business operations. Yet, more research needs to be conducted from the perspective of individuals responsible for implementing DT initiatives in their daily work, such as faculty and staff. This study investigates the relationship between digital readiness in education and the constructs outlined in the Unified Theory of Acceptance and Use of Technology (UTAUT) model. We employed a purposive, non-probabilistic sampling strategy to gather data, resulting in 165 observations. The experimental results indicate a significant positive relationship between behavioral intention to adopt digital trans- formation and the behavior of applying digital transformation at work, perceived effectiveness of digital transformation adoption, and facilitating conditions, all in line with the UTAUT model. However, we did not find a significant relationship between effort expectancy or social influence and behavioral intention to adopt dig- ital transformation. Understanding the factors that impact digital readiness enables universities to develop targeted interventions and support services to promote the successful implementation of DT initiatives in education.

KEYWORDS:

Digital Readiness, Digital Transformation, Education, Technology Adoption, UTAUT

1 | INTRODUCTION

Digital transformation (DT) is a trending term used extensively in recent years due to the rapid advancements in digital technologies[1–3]. DT refers to the incorporation of digital technologies into all facets of the activities of an organization, resulting in significant changes to how it operates and delivers value to its stakeholders. As a result of its ability to improve efficiency, lessen expenditures, and enhance users' overall satisfaction, DT offers numerous advantages to multiple sectors, such as business, healthcare, and marketing[1, 4]. Education is no exception to this trend, as institutions are starting to utilize emerging technologies to transform how they operate and deliver education[3, 5]. For example, universities are using online learning platforms to offer courses to students who are not physically present on campus, and they are also using data analytics to personalize learning experiences for students[6, 7]. While DT promises to revolutionize the entire education system, it also faces many challenges, such as resistance to change, lack of digital skills among faculty and staff, and concerns over data privacy and security[8, 9].

To tackle these challenges, firms or organizations spend a lot of effort and funding to decrease drawbacks and foster innovation. For example, China has implemented a strategic initiative to modernize its education system, which aims to promote the integration of intelligent technology in education and enhance teacher professional development opportunities[10]. Comparably, the University of Michigan took the initiative to establish the Digital Innovation Greenhouse[11]. This innovative project was designed to offer faculty and staff various resources and assistance, enabling them to conceive and develop inventive digital solutions specifically tailored to enhance teaching and learning experiences. In the same vein, with practitioners, researchers also step into finding innovative solutions to mitigate the problem. For example, the paradigm for digital transformation in higher education was established by researchers at the University of Edinburgh, and it emphasizes teamwork, visionary leadership, and an openness to new ideas[12]. However, more work needs to be done from the perspectives of the doers, such as faculty and staff who are implementing DT initiatives in their daily work. Viewing from these perspectives is important as it allows practitioners to identify their challenges and the support they need to overcome them[7, 13, 14]. It also benefits peers in sharing their experiences and best practices.

Thus, this research aims to investigate the relationship between digital readiness in education and the factors outlined in the Unified Theory of Acceptance and Use of Technology (UTAUT) model[15]. The UTAUT model is a widely used theoretical framework for understanding user acceptance and adoption of technology by analyzing the factors that influence digital readiness, such as performance expectancy, effort expectancy, social influence, and facilitating conditions. This study aims to provide insights into how universities can better support faculty and staff in adopting and utilizing digital technologies for teaching and learning. By understanding the factors influencing digital readiness, universities can develop targeted interventions and support services to promote the successful implementation of DT initiatives in education.

2 | PREVIOUS RESEARCHES

Laorach and Tuamsuk[16] conducted a comprehensive study focusing on the determinants that led to the successful implementation of digital transformation within Thai universities. By conducting an experiment involving 495 administrators, the researchers identified six critical factors that played a pivotal role in influencing the triumph of digital transformation in this specific setting. These factors encompassed digital culture, digital strategies, management processes, organizational leadership, digital technologies, and the involvement of staff members. Similarly, Tungpantong et al.[17] researched the critical factors for successful university digital transformation. Three hundred government employees were included in the study. Six components were identified as essential to the digital transformation process: plans, procedures, services or products, individuals, data, and technology.[18] conducted a comprehensive assessment to examine the degrees and impact of computer anxiety and digital preparedness on academic participation among undergraduate students. The findings revealed noteworthy associations between gender, age, internet usage, and students' computer anxiety and digital preparedness. Male students demonstrated superior information-sharing behavior and skills compared to their female counterparts. Furthermore, the study indicated that students' computer anxiety decreased as they advanced. The results also emphasized that higher internet usage levels correlated with enhanced digital preparedness for academic engagement among students.

Using qualitative interviews and thematic analysis, Goarty and Gupta[19] explored factors influencing digital transformation in administrative and academic processes in higher educational institutions. Results show that organizational and technological factors dominate administrative processes, while environmental and teachers' knowledge-related factors drive academic transformation. Deja et al.[20] conducted a study that examined the relationship between factors linked to digital transformation, such as information literacy and digital literacy in academic librarianship, and how they affected information culture and information management strategies. The study highlighted that information literacy was fundamental to empowering academics and that a high level of self-efficacy could lead to a proactive information culture, which prepared academics for digital transformation and improved information use outcomes. Academic libraries could become a transformative force in addressing university digital changes by promoting information literacy outcomes. Nguyen et al.[3] conducted a study aimed at understanding the latent

TABLE 1 General information about respondents (N = 165).

Variable	Item	Count	Proportion
Gender	Male	79	47.88
	Female	86	52.12
Age	18-25	6	3.6
	26-35	75	45.45
	36-45	51	30.90
	Over 45	33	20.05
Occupation	Education	53	32.12
	Public sector	112	67.88
Living area	Rural and mountainous areas	89	53.94
	City centers	48	29.09
	District and town areas	28	16.98

variables that influenced digital transformation readiness among 97 participants in a digital transformation training class. The results of a 12-question survey showed that four major factors - awareness, facilitating conditions, knowledge, and behavioral intention - influenced preparedness. These factors accounted for 61% of the variance in the data, with behavioral intention being the most influential factor. Nguyen et al.[21] investigated the readiness of Vietnamese high schools for digital transformation, focusing on high school teachers' preparedness. The study found a positive level of readiness for digital transformation in Vietnamese general education institutions, with only the Change valence factor showing a significant correlation. These findings will be valuable for teachers, researchers, and school administrators seeking to implement digital transformation in education.

Numerous research studies have investigated the influential factors of digital transformation within educational institutions[3, 16–21]. These studies have identified various factors that play a significant role in the process. While certain studies have focused on assessing the preparedness of high school teachers, others have examined the readiness of universities and academic libraries for digital transformation[20]. The insights derived from these studies can prove invaluable for teachers, researchers, and school administrators seeking to implement digital transformation effectively in education. Nonetheless, further research is necessary to explore additional factors derived from the Unified Theory of Acceptance and Use of Technology (UTAUT) model that may influence digital transformation within educational institutions.

3 | MATERIAL AND METHOD

3.1 | Research Design and Participants

This article focuses on officials and employees who participated in a training program to enhance their qualifications and digital transformation skills in education between June 2022 and December 2022. Upon completing the course, students received a survey through Zalo to gather their feedback. The survey questions were created using Google Forms, consisting of a total of 22 questions, including four relating to basic information (such as age, gender, and occupation) and 18 regarding issues surrounding digital transformation. As the participants selectively enrolled in the training, a purposeful, non-probabilistic sampling strategy was employed to collect data.

3.2 | Data Collection

To measure the participants' level of agreement with each question, a five-point Likert scale was utilized (1: Disagree, 2: Disagree, 3: Neutral, 4: Agree, 5: Agree). The questionnaire was adapted from Venkatesh's documents[15], translated into Vietnamese, and tailored to fit the research context. An example of a question related to effort expectations is (EE1) "Do you believe that the tools and software are useful for your current job?" while a question regarding favorable conditions (FC1) is "Does the agency where you work have adequate infrastructure for digital transformation?". One of the questions related to the intention to act (BI1) is "Are you prepared to undertake digital transformation within the next year?" and one of the questions related to social influence (SI1) is "Do you feel comfortable attending classes with other students?".

Table 1 presents data on the participants' sex, age, sector, and region of residence. Of 188 responses, 23 were invalid, as only one type was selected, leaving 165 valid responses. Of these, 79 were male and 86 were female, indicating a relatively even gender distribution. Participants' ages ranged from 18 to over 45 years old, with 45.45% of the participants being between the ages of 26 and 35. The education and public administration sectors accounted for 32.12% and 67.88% of the total survey participants.

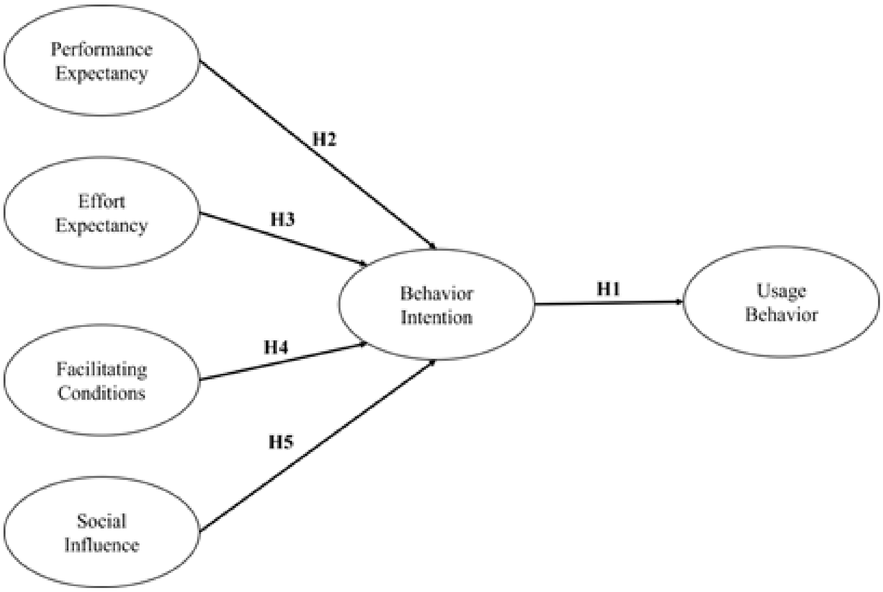

FIGURE 1 UTAUT model for digital transformation adoption behavior.

Rural and mountainous areas had the largest respondents, accounting for 53.94% of the total, followed by city centers (29.09%) and district and town areas (16.98%). These results suggest that the participants were diverse and adequately represented the population characteristics, ensuring the reliability of the data analysis. The data can be used to develop relevant programs and policies and for researchers and professionals interested in the population characteristics of the studied area to analyze advanced data models.

3.3 | Data Analysis

The collected survey data was analyzed using the R lavaan package[22], employing structural equation modeling as the data analysis method. The research hypotheses for the UTAUT model are as follows:

H1 Hypothesis one: Behavioral intention to adopt digital transformation (BI) has a positive and statistically significant impact on the behavior of applying digital transformation at work (UB).

H2 Hypothesis two: Perceived effectiveness of digital transformation adoption (PE) has a positive and statistically significant impact on behavioral intention to adopt digital transformation (BI).

H3 Hypothesis three: Expectation of effort towards digital transformation (EE) has a positive and statistically significant impact on behavioral intention to adopt digital transformation (BI).

H4 Hypothesis four: Facilitation conditions (FC) positively and statistically significantly impact behavioral intention to adopt digital transformation (BI).

H5 Hypothesis five: Social influence (SI) has a positive and statistically significant impact on behavioral intention to adopt digital transformation (BI).

The research hypotheses are visually presented in Fig. 1 . There are four independent variables, i.e., Performance Expectancy, Effort Expectancy, Facilitating Conditions, and Social Influence. There are two dependent variables, i.e., Behaviour Intention and Usage Behaviour.

TABLE 2 The description of the data of the survey questionnaire.

Indicator	Mean	σ	Kurtosis	Deviation
PE1	4.05	0.85	-0.69	-0.45
PE2	4.30	0.88	1.22	-1.21
PE3	4.34	0.89	0.76	-1.20
EE1	4.37	0.80	0.95	-1.20
EE2	4.57	0.77	1.57	-1.63
EE3	4.36	1.04	1.48	-1.53
SI1	4.76	0.59	5.60	-2.53
SI2	4.67	0.63	2.89	-1.89
SI3	4.71	0.59	3.93	-2.09
FC1	3.71	0.90	-0.62	-0.06
FC2	3.75	0.98	-0.60	-0.27
FC3	3.74	0.92	-0.56	-0.23
BI1	3.75	0.89	-0.54	-0.16
BI2	3.84	0.84	-0.72	-0.18
BI3	4.02	0.91	-0.88	-0.44
UB1	4.04	1.01	0.10	-0.87
UB2	4.29	0.79	0.46	-0.87
UB3	4.54	0.77	5.29	-2.09

4 | RESULTS

This section presents two analysis results. The first subsection describes the descriptive analysis result. The second subsection describes outcome of the UTAUT model.

4.1 | Descriptive Analysis

The survey data is presented in Table 2 , displaying the indicators' mean, standard deviation, kurtosis, and deviation. This analysis aims to provide insight into the distribution of these indicators and offer comments on the data. The table shows the distribution of PE, EE, SI, FC, BI, and UB indicators. The mean values of these indicators range from 3.71 to 4.76, with standard deviations from 0.59 to 1.04. SI1 has the highest average value of 4.76, whereas PE1 has the lowest value of 4.05. The standard deviations of these indicators are generally moderate to high, with only UB1 and UB2 having lower values than the others. The kurtosis coefficient indicates the distribution of the indicators. PE2, PE3, EE1, EE2, EE3, and SI3 have positive kurtosis coefficients, indicating that their distributions are narrower than the normal distribution.

On the other hand, SI1, SI2, and UB3 have negative kurtosis coefficients, indicating that their distributions are wider than the normal distribution. Additionally, we should consider the indicators' deviations, which are calculated by dividing the standard deviation by the distance between the mean and the maximum or minimum value in the distribution. The indicators SI1 and UB3 have larger deviations than the others, indicating that their distributions have longer tails than the normal distribution.

4.2 | Structural Equation Modeling

All the indicators listed in Table 3 , namely PE1, PE2, PE3, EE1, EE2, EE3, SI1, SI2, SI3, FC1, FC2, FC3, BI1, BI2, BI3, UB1, UB2, UB3, have a p-value of 0, indicating their statistical significance and importance in the model. The weight of each indicator is determined by a real number between 0 and 1, which represents the extent of its impact on the model results. These indicators have varying weights, allowing for the evaluation of the influence of each variable on the model's outcomes. It is worth noting that the indices do not follow a normal distribution, as indicated by the "None" label in the normal distribution column of Table 3 . This could affect certain statistical operations and interpretation of results. However, the model can still be used effectively in some cases despite non-normal distribution.

The RMSEA index, which measures the fit between the model and the data[23], is 0.078. The RMSEA ranges from 0 to 1, with values closer to 0 indicating a better fit between the model and the data. A low RMSEA value implies that the model accurately represents the data[23]. Moreover, the SRMR index has a value of 0.377, which is another measure of the fit between the model and the data. The SRMR ranges from 0 to 1, with values closer to 0 indicating a better fit between the model and the data. A low SRMR value implies that the model accurately represents the data.

TABLE 3 The indicator weights and significance.

Indicator	Weight	p-value	Normal Distribution
PE1	0.8377	0	None
PE2	0.7578	0	None
PE3	0.7381	0	None
EE1	0.7429	0	None
EE2	0.6077	0	None
EE3	0.6657	0	None
SI1	0.4493	0	None
SI2	0.5727	0	None
SI3	0.5428	0	None
FC1	0.866	0	None
FC2	0.8736	0	None
FC3	0.8776	0	None
BI1	0.8702	0	None
BI2	0.8607	0	None
BI3	0.8349	0	None
UB1	0.8246	0	None
UB2	0.774	0	None
UB3	0.6342	0	None

TABLE 4 The UTAUT model coefficients and confidence intervals.

Indicator	Coefficient	ci.lower	ci.upper	SE	Z	p
PE1	0.744	0.634	0.854	0.056	13.233	0.000
PE2	0.952	0.857	1.048	0.049	19.469	0.000
PE3	0.509	0.340	0.678	0.086	5.915	0.000
EE1	0.768	0.633	0.904	0.069	11.091	0.000
EE2	0.738	0.601	0.875	0.070	10.567	0.000
EE3	0.326	0.131	0.521	0.099	3.282	0.000
SI1	0.803	0.716	0.891	0.045	17.999	0.000
SI2	0.918	0.851	0.985	0.034	26.738	0.000
SI3	0.738	0.636	0.841	0.052	14.140	0.000
FC1	0.051	0.399	0.697	0.178	0.288	0.000
FC2	0.406	0.172	0.639	0.119	3.408	0.000
FC3	0.596	0.310	0.881	0.146	4.086	0.000
BI1	0.538	0.365	0.712	0.089	6.075	0.000
BI2	0.910	0.822	0.998	0.045	20.290	0.000
BI3	0.859	0.769	0.949	0.046	18.667	0.000
UB1	0.762	0.596	0.929	0.085	8.954	0.000
UB2	0.903	0.726	1.081	0.091	9.969	0.000
UB3	0.267	0.073	0.461	0.099	2.700	0.000

Table 4 displays the outcomes of the UTAUT model run via Lavaan software. The table lists the different indicators, their coefficients, the lower and upper limits of the 95% confidence interval, the standard error, the Z-statistic value, and the p-value. All estimated coefficients have a p-value less than 0.05, indicating their statistical significance and importance in measuring technology adoption and use according to the UTAUT model[23]. Positive coefficient values of indicators such as PE1, PE2, EE1, EE2, SI1, SI2, BI1, BI2, UB1, and UB2 suggest that these factors favor acceptance and digital transformation behavior.

Table 5 presents the results of a structural equation model, where paths are computed from coefficients and their corresponding confidence intervals. The coefficients indicate the degree of influence of independent variables on the dependent variable[23]. Positive coefficients suggest a positive correlation (i.e., when one variable increases, the other increases), while negative coefficients suggest a negative correlation (i.e. when one variable increases, the other decreases). The coefficients' confidence intervals indicate the certainty level of their estimates. The p-value indicates the probability of the hypothesis that the coefficient differs from zero[23]. If the p-value is less than 0.05, we can conclude that the coefficient is statistically significant, meaning there is a significant correlation between the two variables. If the p-value is greater than 0.05, we cannot reject the hypothesis that the coefficient equals zero, meaning there is no significant correlation between the two variables.

The path from FC to BI has a coefficient of 0.784, with a confidence interval ranging from 0.282 to 1.286 and a p-value of 0.002. This indicates a significant positive correlation between these variables, confirming hypothesis H4. The path from PE to BI has a coefficient of 0.535, with a confidence interval ranging from 0.041 to 1.029, confirming hypothesis H2. Among

TABLE 5 The path coefficients of a structural equation model.

Hypotheses	Coefficient	ci.lower	ci.upper	SE	Z	p
BI → UB (H1)	0.371*	0.185	0.556	0.095	3.913	0.000
FC → BI (H4)	0.784*	0.282	1.286	0.256	3.060	0.002
EE → BI (H3)	-0.054	-0.515	0.407	0.235	-0.229	0.819
PE → BI (H2)	0.535*	0.041	1.029	0.252	2.121	0.034
SI → BI (H5)	0.24	-0.077	0.561	0.163	1.487	0.137

the relationships between variables, the relationship between FC and BI has the highest correlation coefficient of 0.784, with a significance level of $p<0.01$. This suggests that FC significantly impacts BI, with each unit increase in FC associated with a relatively large increase in BI. The relationship between PE and BI also achieves a significance level of $p<0.05$, with a correlation coefficient of 0.535, indicating a relatively strong relationship between these variables. Similarly, the relationship between BI and UB achieves a significance level of $p<0.05$, with a correlation coefficient of 0.371 (H1). The relationship between EE and BI has a correlation coefficient of -0.054, which is not statistically significant, indicating no significant relationship between these variables and rejecting hypothesis H3. The relationship between SI and BI has a correlation coefficient of 0.24, which is not statistically significant (rejecting hypothesis H5) but still suggests an interaction between the two variables.

Overall, these results provide an overview of the relationships between variables in the dataset and can be used to develop predictive models or to understand further factors affecting BI.

5 | DISCUSSION

In this study, we conducted path analysis using the UTAUT model to examine the relationships between various constructs. This discussion aims to provide a thorough analysis of the results presented in Table 5 , compare them to prior research, and highlight the implications of the findings.

[H1] BI → UB: Our analysis revealed a significant positive relationship (path coefficient of 0.371*, $p < 0.001$) between behavioral intention and usage behavior. This suggests that individuals with a stronger intention to engage in digital transformation are more likely to participate in the actual implementation of the technology. This finding is consistent with previous studies that have consistently found a positive association between behavioral intention and actual behavior, thus supporting the validity and reliability of the UTAUT model[15].

[H4] FC → BI: Our results show a significant positive relationship (path coefficient of 0.784*, $p = 0.002$) between FC and BI. This suggests that when individuals perceive that necessary conditions, such as technical support or resources, are available to facilitate digital transformation, their intention to adopt the technology increases. This finding corroborates prior research that has emphasized the importance of facilitation in influencing behavioral intention [20].

[H3] EE → BI: Our analysis did not reveal a significant relationship (path coefficient of -0.054, $p = 0.819$) between effort expectations and behavioral intentions. This implies that perceived ease of use or the effort required to use a technology for digital transformation may not significantly influence individuals' intentions to adopt the technology. These results are somewhat surprising and contradict the findings of several previous studies that have identified a positive association between effort expectations and behavioral intentions. However, it is important to consider the wide confidence interval and the possibility of type II error when interpreting these non-significant results[15].

[H2] PE → BI: Our analysis revealed a significant positive relationship (path coefficient of 0.535*, $p = 0.034$) between performance expectations and behavioral intentions. This implies that individuals who perceive that digital transformation will lead to improved performance or results are more likely to have intentions to adopt the technology. This finding is consistent with prior research that has consistently supported the effect of performance expectations on behavioral intention[15].

[H5] SI → BI: Our analysis did not reveal a significant relationship (path coefficient of 0.24, $p = 0.137$) between social influence and behavioral intention. This suggests that the influence of social factors, such as opinions and recommendations from others, may not significantly impact individuals' intentions to adopt technology. However, it is worth noting that the p-value is relatively close to the significance threshold, indicating the possibility of a weak relationship. These findings differ from previous studies that reported a positive association between social influence and behavioral intention [15].

Upon comparing the results of our study with those of previous research, we found both consistent and inconsistent findings. The pos- itive relationships observed between BI and UB (H1) and PE and BI(H2) align with numerous studies that have established the predictive power of BI in technology adoption [15]. However, the need for a significant relationship between EE and BI (H3) contradicts prior studies that reported a positive association. This divergence could be attributed to differences in sample characteristics, technological contexts, or measurement scales employed across various studies. Additionally, the absence of a significant relationship between SI and BI (H5) is inconsistent with previous research that highlighted social factors' impact on an individual's intention to adopt technology [15].

The results of our path analysis using the UTAUT model have significant implications for researchers and practitioners in digital transformation and education. Firstly, the significant positive relationship between BI and UB (H1) emphasizes the importance of measuring and understanding individuals' intentions as a reliable predictor of their digital transforma- tion. This finding suggests that interventions or strategies to enhance individuals' digital transformation intentions can effectively translate into higher adoption rates.

Secondly, the significant positive relationship between PE and BI (H2) underscores the need to prioritize the design of technologies that provide clear benefits and improvements to performance or user outcomes. Highlighting technology's advantages and positive outcomes can enhance individuals' intentions to adopt digital transformation. Furthermore, the lack of a significant relationship between EE and BI (H3) raises interesting questions and calls for further investigation. While our study did not support a direct effect of perceived effort or ease of use on BI, exploring potential moderating factors or mediating mechanisms that may influence behavioral intentions and explaining this relationship more comprehensively is crucial. Future research may delve into individual differences or contextual factors that influence the impact of EE on BI.

Additionally, the insignificant relationship between SI and BI (H5) suggests that the role of social factors in digital transformation adoption may be context-dependent or influenced by other variables. Understanding the complexities of social influence and its interaction with individual motivations and perceptions can help refine strategies that drive technology adoption and use. Future studies may explore the role of specific social factors, such as social norms or social networks, in shaping individuals' behavioral intentions.

6 | CONCLUSION

In this study, we utilized path analysis through the UTAUT model to investigate the associations among factors in technology adoption for digital transformation. Our findings provide valuable insights and have significant implications for researchers and practitioners. While some established relationships were confirmed, others were challenged, underscoring the need for further research and exploration across diverse contexts. The UTAUT model remains a powerful tool for compre- hending the factors that influence technology adoption for digital transformation and can inform the development of effective interventions and strategies to promote adoption and use across varied contexts.

CREDIT

Vinh Nguyen: Conceptualization, Methodology, Writing - Original Draft Preparation, Writing - Review and Editing, and Supervision. **Chuyen Nguyen**: Formal analysis, Investigation, and Funding Acquisition. **Cuong Do**: Writing - Review and Editing, Formal Analysis, Investigation, and Funding Acquisition. **Quynh Ha**: Formal analysis, investigation, and Resources.

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