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Determinants of Digital Transformation Adoption in Education: An Evaluation of a Post-pandemic Case Study in Vietnam

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ABSTRACT
In recent years, digital transformation (DT) has emerged as a subject with numerous promise advantages across several industries. Prior papers focused mostly on identifying benefits and obstacles, but less is known about validation, particularly in the educational sector. Thus, the objective of this study is to fill the gap by examining the factors that influence the acceptance of digital transformation in the education setting. 318 prospective adopters of DT consented to participate in this research by completing an online survey through Google Form. These samples were divided into 159 individuals for exploratory factor analysis (EFA) and 159 observations for confirmatory factor analysis (CFA). The EFA favored a five-factor model, which was shown to explain over 69% of the data variance. The tentative names for these hidden variables were policy, efficiency, knowledge, facilitating conditions, and behavioral intention. Two items were excluded from the scale measurement due to cross-loading on other factors. The findings of the CFA confirmed and validated the five-factor model, with all test measures meeting the predefined thresholds, indicating an acceptable fit. As opposed to evaluating individual indicators, the findings of this study present five crucial topics for instructors, educators, and policymakers to examine, and they also provide a foundation for interested researchers to perform further studies.

Keywords: digital transformation, exploratory factor analysis, confirmatory factor analysis, post-pandemic, research model validation.

INTRODUCTION

Recent years have seen a global shift in social interaction, communication, and behavior due to the proliferation of cutting-edge technologies, such as sensors, the internet of things, blockchains, big data, and artificial intelligence (Ahmad et al., 2022; Buendicho, 2023; Jung et al., 2020; Machmud et al., 2021; Yoo et al., 2020). One of the emerging terms that has been used to characterize these shifts is digital transformation. Although the term "digital transformation" (DT) has been used extensively in academic circles, its definition remains vague across disciplines (Heavin & Power, 2018; Legner et al., 2017; Vial, 2021). For example, Heavin and Power (2018) described DT as a phenomenon in the business world in which technology was utilized to dramatically enhance a company's performance or reach, ultimately benefiting the consumer in every possible way. Alternatively, Vial (2021) examined DT from a purely technological point of view, this may be interpreted as an organizational transition to platforms centred on big data, the internet of things, cloud computing, social media, and artificial intelligence. Legner et al. (2017) expressed DT as the shifts necessitated by the introduction of IT in order to (at least partially) automate processes. According to a recent analysis (Vial, 2021), there are at least 24 different meanings for the term DT. This indicates that there is a rising interest in DT and that academic perceptions are not homogeneous. In the context of this article, DT is viewed as the transformation of a conventional method into a new one through the utilization of digital technology.

DT has been a priority for many businesses and government several countries, particularly in the technology and finance sectors (Khanna et al., 2022). For example, JPMorgan Chase (located in the United States) has made significant investments in digital transformation (Can, 2022) and is promising to become the most digitally advanced financial firms in the world. Similarly, Amazon has used data analytics to improve its supply chain management (Resca & Spagnoletti, 2014), while Microsoft has invested in cloud computing to deliver faster, more efficient services (Guinan et al., 2019). In the United Kingdom, DT has been a key focus for the government since 2017, with Digital Skills Partnership initiatives to fostering digital skills (Eynon, 2021). As such, the GovTech Catalyst was launched as part of the plan. Some international examples of DT implementers are Alibaba and Tencent from China (Zhang-Zhang et al., 2020) and Smart Nation from Singapore (Ho, 2017).

With a growing interest in DT, many researchers around the world have investigated DT from various domains (Aghayari et al., 2022; Li, 2020; Nguyen, 2022; Schallmo et al., 2017). For instance, Schallmo et al. (2017) offered a pathway to DT in the business sector that included five phases (reality, aspiration, potentiality, fit, and implementation) and four enablers (data, automation, digital access, and networking). It was anticipated that their findings would contribute to the body of knowledge and assist businesses in optimizing their present strategies and developing distinct competitive advantages. In the same vein, Li (2020) proposed three DT approaches that enterprises would have (i.e., experimentation, sequential incremental adjustments, and a portfolio of transitory advantages), and as such, the primary target audience for these suggestions are potential adopters of digital transformation. Using the Delphi technique, Aghayari et al. (2022) identified six essential Telecom Industry components (government, business model, culture, technology, customer, and workforce) and twenty indicators. In the educational domain, Bogdandy et al. (2020) surveyed students regarding digital education and changes in Hungary. This study varied from previous papers in which DT was used to investigate the short-term effects of Covid-19. Focusing on technical preparedness and infrastructure, their findings indicated that half of the questioned students would like to continue utilizing DT in the future, with the majority preferring to utilize their own devices despite certain device software compatibility issues. Giang et al. (2021) investigated four critical components affecting the preparedness of DT in higher education institutions (i.e., education program, learners, training services, and government), and that these factors will be used to construct a theoretical model in later research. In their study, Geroche and Yang (2022) emphasized the importance of readiness, comprehensiveness, and trans methodology in reaction to covid lockdowns. Additionally, the results verified Kotter's eight-step process for expediting the change to DT. The aforementioned papers indicated that DT was examined from a variety of scholarly viewpoints, with a number of suggestions.

As the number of articles has increased, interested academics have been synthesizing the applications of DT in general or within their respective fields. For instance, Reis et al. (2018) conducted a literature review of DT from 1968 to 2017. Their findings, based on 206 papers, revealed that DT began to emerge in earnest in 2014 and that the United States and Germany were the most active nations researching this area. In addition, they identified five primary research fields of DT, with information systems and business economics among the most active, followed by education (8%), management science (4%), and government (1%). In educational settings, Benavides et al. (2020) summarized 19 publications in DT from 2016 to 2019. Their findings revealed that, among the 11 dimensions, the interventions of DT had the greatest impact on teaching, while marketing was least affected in higher education. In the same vein, Cerdá Suárez et al. (2021) investigated the perceptions of Latin America toward DT in higher education. Based on evidence from various sources, the authors reported that most DT adopters were leaders in general and that Covid-19 accelerated the process of DT. In addition, the report indicated that higher education institutions need financial resources to evaluate metrics and indicators that take into account a variety of cultural, social, environmental, and economic factors.

Even though there are a lot of scientific publications (Auer & Tsiatsos, 2018; Benavides et al., 2020; Reis et al., 2018; Verhoef et al., 2021), they all use the same methodology to investigate the advantages, difficulties, and prospective research areas of DT. Little is known about the existence of a coherent theoretical foundation or validation of the proposed conceptual model of DT. As a result, there is a significant gap that has to be addressed. Filling this gap or gaining an understanding of a conceptual model is crucial for enhancing the success of a strategy, as it has been intensively researched in several analogous studies (Abubakar et al., 2022; Ahmad et al., 2021; Mohammed & Ismail, 2019). Examining whether DT should be continued or used as a substitute during the Covid-19 pandemic is especially more vital in the context of the post-pandemic period. Thus, the purpose of the current study is to fill this gap by investigating a conceptual model of DT. In other words, this article aims to address the following research questions (RQ):

- RQ1: What are the factors that influence the acceptability of Digital Transformations in education?
- RQ2: How acceptable are these factors as determinants of acceptability of DT in education based on factor analysis tests?

To the best of our knowledge, there is no current publication that addresses these questions, making this an original contribution.

MATERIALS AND METHODS

Research Design

The present research made use of the quantitative research methodology in order to gain a deeper understanding of the underlying dimensions that may contribute to the readiness of prospective DT adopters. To be more specific, an exploratory factor analysis, also known as an EFA, was carried out in order to extract latent variables from the question being addressed. EFA is a statistical method that has seen widespread application in the research community for the purpose of revealing hidden structures in feature sets (Hair, 2009). Since EFA was able to minimize the number of variables while retaining the majority of the information, it was often referred to as a “dimension reduction technique.” To further investigate and verify the discovered dimensions, we will use confirmatory factor analysis (CFA) (Hair, 2009). EFA and CFA both analyze the correlation between observable and latent variables. From there, we may establish which observable components contribute considerably and which do not to the parent hidden variable. Furthermore, convergence and discrimination between variable-structure groupings are observed in both methods. In contrast to EFA, where the observed variables included in the EFA analysis will be interpreted as having equal roles and it is unknown which observed variable belongs to which latent variable, the observed variables included in the CFA were all identified from the outset of the latent variable and only the role of the observed variable within that one latent variable was considered (Tabachnick et al., 2007). The dataset was randomly split into two parts, one for EFA and one for CFA, so that analysis could be performed for both methods.

Sample and Data Collection

The population of interest in this study are prospective adopters of DT, and those who participate in the nation-wide DT training program on a large scale constitute the accessible population. The purposive sampling technique was employed to recruit participants from the accessible population. Google Form was used as a means to administer questionnaires and obtain data. Before the actual survey was carried out, the participants were given information on its aim, the sort of data that would be gathered, how the data would be stored and distributed, and their freedom to withdraw their participation at any time. The Institutional Review Board (IRB) approval was not needed because the survey did not request any personally identifiable information. The survey was conducted with the help of three training programs over the course of six months, from June to December 2022. Participants were invited to fill out the online survey after the course was finished. The questionnaire consists of two sections: the first section includes general information of the participants, and the second section comprises 19 questions asking about their perceptions of digital transformation. A five-point Likert scale was employed to measure the level of agreement with respect to each question (1: Strongly Disagree, 2: Disagree, 3: Neutral, 4: Agree, and 5: Strongly Agree). The questions were modified from prior research (Baabdullah, 2020; Nguyen et al., 2022; Williams et al., 2015) and justified within the context of the present investigation. They were tested for consistency and face validity by two specialists in the domains before they were administered to respondents. If any value was missing, the entire record was excluded. In addition, responses with anomalous patterns (outliers), such as a score of all 5, would be eliminated. The current study has a sample size of 318/19, or a 17:1 observation-to-variable ratio in total. As such, there are 159 observations and 19 variables in the data used for EFA and CFA, respectively, for an observation-to-variable ratio of 8:1. The literature provides many parameters to aid researchers in determining the appropriate sample size. Sample sizes of 5:1, 10:1, and 20:1 were suggested by Hair (2009), for instance, as acceptable, moderate, and excellent, respectively. The sample size was indicated by a specified number by other researchers, such as 50, 100, 500 or more than 1000 (Bujang et al., 2018). The current research relied on a widely-used criterion developed by Hair (2009), and as such, it was regarded to be of moderate quality.

Data Analysis

For the first research question (RQ1: What are the factors that influence the acceptability of Digital Transformations in education?), a number of criteria were established prior to conducting the actual EFA experiment. The first indicator was the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (or KMO). The KMO coefficient is an index for assessing if factor analysis is acceptable by comparing the total correlation coefficient of two variables to their partial correlation coefficient (Hair, 2009; Tabachnick et al., 2007). The value of KMO ranges between zero and one. A score close to zero indicates that the total partial correlations are more than the sum of the correlations, indicating that the correlations are extensive and do not cluster around a small number of variables. As such, it is infeasible to perform factor analysis. In contrast, a score close to one indicates an excellent fit for factor analysis. Literature work recommended that a score of .90 or more was marvelous, 0.8 - 0.9 was meritorious, 0.7 - 0.8 was average, 0.6 - 0.7 was mediocre, 0.5 - 0.6 was terrible, and less than 0.5 was unsatisfactory. In the context of this study, a score of 0.7 or more would be expected. This is because participants come from various sectors, at different ages and educational levels, thus their perceptions would be varied. The second indicator is the Bartlett's Test of Sphericity - a statistical procedure for investigating the null hypothesis that there is no correlation between the study's variables (Hair, 2009; Tabachnick et al., 2007). In other words, it assumes a perfect correlation between each individual variable and itself, but no correlation between any of the variables. Here, the study is attempting to uncover underlying patterns in the data, thus it is important to highlight relevant correlations. Therefore, at the 0.05 alpha level, it was expected that the null hypotheses would be rejected (p-value < 0.05). For the number of factors to be extracted and retained in the final model, an eigenvalue would be served as an indicator. The eigenvalue is the amount of variation that can be accounted for by a certain principal component or factor (Hair, 2009; Tabachnick et al., 2007). Each component's eigenvalue can be described as the total squared component loadings over all items; these loadings, in turn, reflect the amount of the variance in each item that can be explained by the principal component. When the eigenvalue is close to 0, all the variation may be explained by the first component, indicating multicollinearity among the items. If, on the other hand, the eigenvalues are nonnegative, that is a favorable indicator. Literature work suggested that only those variables with eigenvalues of 1.00 or above are considered to be of relevance to the analyst in the vast majority of settings. Therefore, the current research favors retaining components with eigenvalues greater than 1.00. The final indicator is factor loading – standardized regression weight representing the correlation between the observed variable and the factor. It is suggested that factor loading in EFA be greater than 0.5 in order for the observed variable to have statistical significance.

For the second research question (RQ2: How acceptable are these factors as determinants of acceptability of DT in education based on factor analysis tests), several parameters were set up in advance of the actual CFA experiment. The two indicators were the scale measurement's reliability and validity. Construct reliability (CR) and average variance extracted (AVE) will be utilized in this context. CR refers to the degree to which a set of indicators accurately represents an intangible concept that is meant to be measured (Hair, 2009; Tabachnick et al., 2007). In the contemporary theories of validity, CR is the primary focus of validity studies, superseding evidence of other forms of validity, such as content validity and criterion validity. Literature reviews indicated that a value of CR larger than 0.7 was preferable, therefore we used it as our cutoff. AVE examines how closely related answers to a set of questions coincide in their representation of an abstract idea. It is the average percentage of inter-item variation that may be accounted for by common factors. As a general rule, it is recommended that the AVE be at least 0.50 in order to provide enough convergence (Hair, 2009; Tabachnick et al., 2007). Thus, we used 0.50 as out cutoff for AVE. For the assessment of the CFA results, several measures were reported, such as Degree of Freedom (CMIN/DF), Goodness of Fit Index (GFI), Adjusted Goodness of Fit Index (AGFI), Normed Fit Index (NFI), Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), and PCLOSE. CMIN/DF is the smallest variance divided by its degrees of freedom. It was suggested that this ratio serve as a measure of similarity between the hypothetical model and the sample data. Numerous reports have advocated using ratios somewhere between 2–5 to indicate a reasonable fit. As such, the current study follows this range. GFI is a statistical measure that evaluates how well an estimated model matches an observed covariance matrix. It was recommended that this index should be greater than 0.90 for a reasonable fit (Hair, 2009; Tabachnick et al., 2007). AGFI is a similar statistic with GFI that accounts for the degrees of freedom with which the model may be evaluated. It is commonly acknowledged that AGFI's score of 0.90 or higher indicates well-fitting models. NFI compares the Chi-Square value (χ^2) of the model to the Chi-Square value (χ^2), where the null hypothesis is that all of the measurement items are random variables, to determine if the model is statistically significant. This metric's values can be anywhere from 0 to 1, but a value of 0.90 or above is generally seen as being indicative of a satisfactory degree of fit (Hair, 2009; Tabachnick et al., 2007). The CFI is a revised version of the NFI that takes sample size into consideration. Literature research has indicated that a score greater than 0.90 is necessary to ensure that incorrectly defined models are not accepted. The RMSEA is used to evaluate how well the model fits the covariance matrix of the population, given optimal but uncertain parameter estimates. Then, it was suggested that RMSEA values between 0.08 and 0.10 indicate a moderate fit, whereas values below 0.08 indicate a good fit. PCLOSE is a "p-value" for assessing the proposition that the RMSEA of a population is less than 0.05. Thus, PCLOSE values more than .05 suggest a excellent fit, whereas PCLOSE values greater than .01 indicate an adequate fit (Hair, 2009; Tabachnick et al., 2007). IBM SPSS (v25.0) was used for the EFA, while IBM Amos (v20.0) was used for the CFA.

RESULTS AND DISCUSSION

Descriptive Analysis

The general information of the participants is reported in Table 1 which shows that females make up 39.62% of the sample while men account for 60.38% of the total. The disparity between men and women was attributed to the fact that the majority of men were in charge of DT, which entailed information technology. More than one third of the respondents are between the ages of 18 and 25 (38.36%), almost half of the participants are between the ages of 26 and 35 (45.91%), and just a small number of the subjects are between the ages of 36 (11.95%) and 45 (3.77%). In terms of educational attainment, more over half of respondents (59.12%) have a master's degree, followed by those with an undergraduate degree (39.94). Only three participants have a doctorate. In terms of demographic statistics, the majority of prospective DT adopters reside in rural regions (53.5%), followed by province or city (28.2%), and then the district (16.2%).

Table 1: General information of the participants

Variable	Item	Frequency	Percentage
Gender	Female	126	39.62
	Male	192	60.38
Age	18-25	122	38.36
	26-35	146	45.91

	36-45	38	11.95
	Over 45	12	3.77
Educational Level	Undergraduate	127	39.94
	Graduate	188	59.12
	PhD	3	0.94
Living Areas	Rural areas	170	53.5
	District	53	16.5
	Province/City	95	28.2
Total		**318**	**100**

In terms of the questionnaires administered to participants, Table 2 displays the mean, standard deviation, skewness, and kurtosis of the survey responses' data. All mean values are above the midpoint of 2.5 (ranging from 3.20 to 3.68), implying that prospective DT adopters have some positive awareness about DT. Standard deviations are between .609 and 0.791, indicating normal widespread of data around the mean. Skewness is between -1.089 and 0.162, suggesting that participants largely tend to agree with questions posed. Kurtosis is between -.202 and 2.281, implying that the centralized distribution is less than normal.

Table 2: Mean, Standard Deviation, Skewness, and Kurtosis of the Samples

	Mean	Std. Deviation	Skewness	Kurtosis
V1	3.35	.771	-.518	1.376
V2	3.45	.743	-.283	.659
V3	3.20	.701	.035	1.618
V4	3.67	.775	-1.089	2.281
V5	3.36	.791	-.206	.595
V6	3.65	.772	-.382	.759
V7	3.67	.698	-.243	.649
V8	3.57	.660	-.203	.723
V9	3.60	.637	-.174	.851
V10	3.52	.762	-.336	1.116
V11	3.55	.777	-.345	.153
V12	3.52	.770	-.622	.619
V13	3.59	.713	-.168	.453
V14	3.39	.711	-.193	.866
V15	3.47	.701	-.401	.378
V16	3.53	.728	-.799	1.565
V17	3.51	.664	.162	-.202
V18	3.60	.647	-.086	-.156
V19	3.68	.609	-.548	.394

Quantitative Analysis

Table 3 provides the results of the KMO and Bartlett's Test. The experimental results showed that the KMO is meritorious ($0.8 < 0.841 < 0.9$). In addition, the Bartlett's Test is statistically significant, with $\chi 2$ (171) = 1486.805, and $\rho < 0.000$.

Table 3: KMO and Bartlett's Test of Sphericity

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.841
Bartlett's Test of Sphericity	Approx. Chi-Square	1486.805
	df	171
	Sig.	.000

The eigenvalue, variance explained, and cumulative variance are shown in
Table **4**, along with a summary of the total variance explained. In this table, five factors were found using the Kaiser criteria (i.e., factors are kept in the model if their eigenvalues are larger than 1). This number was also in accordance with the guidelines (four to six factors). Overall, these five factors accounted for 69.409% of the variation in the data that was collected from 159 potential DT adopters; the remaining variance was attributed to other factors. The present result was in line with the recommendations in the social sciences (about 60 percent),

or other studies (Fauzi et al., 2022), despite the fact that there is no general agreement over the minimum amount of total variation that must be explained.
Table 4 shows that factors 1, 2, 3, 4, and 5 are accounted for 34.384%, 11.024%, 8.968%, 7.895%, and 7.317% of the total variation, respectively.

Table 4: Total variance explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.533	34.384	34.384	6.533	34.384	34.384
2	2.095	11.024	45.408	2.095	11.024	45.408
3	1.704	8.968	54.376	1.704	8.968	54.376
4	1.500	7.895	62.272	1.500	7.895	62.272
5	1.356	7.137	69.409	1.356	7.137	69.409
6	.848	4.462	73.871			
7	.688	3.620	77.491			
8	.670	3.528	81.019			
9	.573	3.016	84.035			
10	.433	2.280	86.315			

In addition to data provided in
Table 4, we also examined examine scree plot (see figure 1). This figure suggests that five factors should be considered while analysing eigenvalue fluctuations (i.e., recognizing the "elbow" in the plot). Comparison of the sixth factor's eigenvalue (.848) to the latent root criterion value of 1.0 indicated that it did not meet the requirements for inclusion. It may be assumed to b e included if the eigenvalue was close to 1. Based on these criteria, we can safely assume that five factors warrant further study.

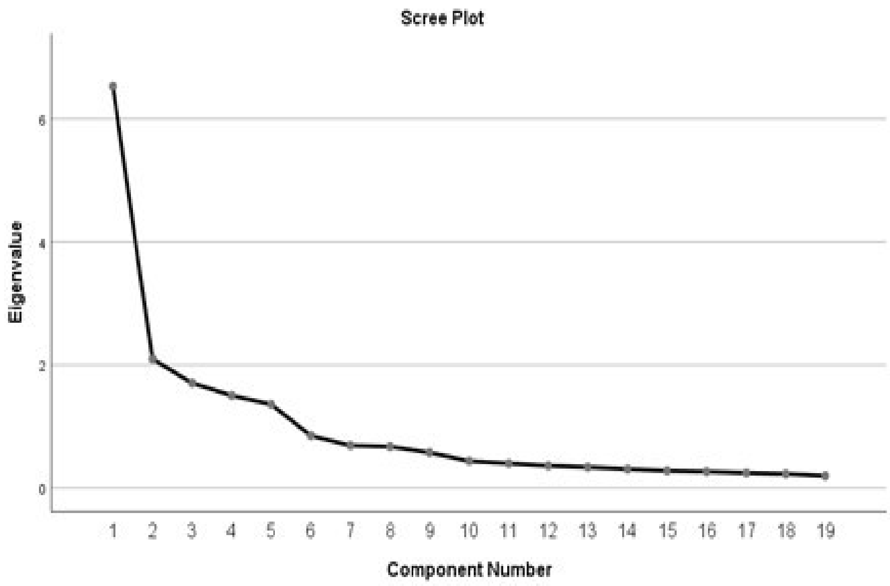

Figure 1: Scree Plot of Eigenvalue vs Component Number

The factor loadings for each factor are shown in Table 5. There is a wide variety of conceivable factor loadings, ranging from .473 to .862. According to Hair (2009), only items that have a factor loading that is at least .45 or above are retained in a sample that has 150 or more. And as can be shown in table 5, all five of these factors are strongly desirable, with over three variables each component scoring above .45. Two items (Q9 and Q10) that exhibit cross-loading will be omitted from the scale and future analysis.

Table 5 Rotated Component Matrix

	Component				
	1	2	3	4	5
V11	.838				
V13	.775				
V07	.680				
V12	.613				
V9	.509	.469			
V8	.473				
V5		.814			
V6		.786			
V10		.565	.404		
V4		.526			
V2			.826		
V3			.796		
V1			.757		
V15				.862	
V16				.853	
V14				.765	
V18					.852
V19					.800
V17					.766
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.					
a. Rotation converged in 7 iterations.					

Table 6 displays the results of EFA in terms of factor name, Cronbach's alpha, and factor loading for each component. Overall, the reliability of the scale in each factor is satisfactory, as indicated by Hair (2009), using a cut-off value of 0.70. Since the majority of the variables on Factor 1 were all conceptually related to the organization's DT policies, Factor 1 was labelled as “Policy.” Factor 2 was tentatively named the “Awareness” factor since the three items that loaded most significantly were all associated with awareness of the presence of DT. Owing to the fact that the three factors that loaded most strongly on Factor 3 were all connected with confidence and knowledge in a manner thought advantageous to potential DT adopters, Factor 3 was named “Knowledge.” Moreover, the three elements that loaded into Factor 4 were all associated with resources that participants are able to use and consult throughout the DT process. Consequently, Factor 4 has been temporarily labelled “Facilitating Conditions.” The label "Behavioral Intention" was derived from the idea that all questions in Factor 5 pertained to future activities that participants intended to pursue.

Table 6 Exploratory Factor Analysis Result

Variable	**Items**	**Factor loadings**
Factor 1. Policy (Cronbach’s alpha α = 0.803)		
V11	My workplace has a well-defined DT policy.	.838
V13	It won't be too difficult for me to modify my behavior to conform to the policies.	.775
V7	In the opinion of my coworkers and friends, I should start adopting DT.	.680
V12	There is a clear DT policy that can be followed.	.613
V8	If my coworkers and colleagues are adopting DT, then I should too.	.473
Factor 2. Awareness (Cronbach’s alpha α = 0.753)		
V5	I have been exposed to DT as part of my training.	.814
V6	I am aware of DT due to the policy in place at my school or workplace.	.786
V4	I am aware of DT through various forms of media promotion.	.526
Factor 3. Knowledge (Cronbach’s alpha α = 0.822)		
V2	I am comfortable expressing my thoughts when it comes to DT in my expertise	.826
V3	I believe that I comprehend DT in the present setting.	.796
V1	I believe I have some understanding of DT.	.757
Factor 4. Facilitating Conditions (Cronbach’s alpha α = 0.854)		
V15	I am prepared to adopt DT with the various devices (such as a smartphone, tablet,	.862

	laptop, and desktop computer).	
V16	When I need help with a DT-related problem, I may contact the relevant IT service providers.	.853
V14	My university or institution have the requisite resources in order to accomplish DT.	.765
Factor 5. Behavioral Intention (Cronbach's alpha α = 0.825)		
V18	I anticipate adopting DT within the next twelve months.	.852
V19	I intend to embrace DT at the earliest opportunity.	.800
V17	I anticipate integrating DT into my work over the next six months.	.766

The reliability and validity of the scale employed in CFA analysis are shown in Table 7. All of Cronbach's alpha values exceed the suggested threshold of 0.7. Similarly, both CR and AVE are more than .7 and .5 respectively, showing that the construct is valid and reliable.

Table 7 Reliability and Validity of the scale measurement

Factor	Items	Cronbach's alpha	CR	AVE
Policy	5	.795	.712	.583
Awareness	3	.749	.710	.515
Knowledge	3	.792	.746	.553
Facilitating Conditions	3	.720	.733	.529
Behavioral Intention	3	.798	.741	.546

Table 8 reports the model fit summary of the CFA. Results from the table provide information that CMIN/DF = 2.186 indicating an excellent criterion. In this experiment, the GFI value (0.858), AGFI value (0.815), and NFI value (0.833) were close to the acceptable levels. Results of various researchers indicated that the small number of participants in the study may attribute to the problem of low score. Scientists suggest that a sample size of 1600 will provide reliable results across all fit indices, despite the fact that larger samples have a greater impact on certain indices than others (GFI, AGFI, NFI, and RMSEA). However, if the sample size is too large, the power of statistics—that is, the capacity to draw conclusions from the small amount of data—will be diminished (V. T. Nguyen & C. T. H. Nguyen, 2022). According to the research (Doll et al., 1994; Segars & Grover, 1993), scores between 0.80 and 0.89 are likewise considered appropriate. It was thus determined that these levels were acceptable. In this context, it is possible to assert that the CFA result validates the model. The RMSEA score (.06) was below the threshold of .08, indicating that the analysis was acceptable. Finally, PCLOSE was considered an excellent fit where its estimate was much higher than the cutoff value.

Table 8 Model Fit Summary

No	Measure	Estimate	Cut-off	Interpretation
1	CMIN/DF	2.186	< 3	Excellent
2	GFI	.858	≥ .95 Excellent ≥ .90 Good ≥ .80 Acceptable	Acceptable
3	AGFI	.815	≥ .95 Excellent ≥ .90 Good ≥ .80 Acceptable	Acceptable
4	NFI	.833	≥ .95 Excellent ≥ .90 Good ≥ .80 Acceptable	Acceptable
5	CFI	.899	≥ .95 Excellent ≥ .90 Good ≥ .80 Acceptable	Good
6	RMSEA	.060	≤ .01 Excellent ≤ .05 Good ≤ .08 Acceptable	Acceptable
7	PCLOSE	.192	≥ .05 Excellent ≥ .01 Acceptable	Excellent

Figure 2 depicts the completed measurement model of potential DT adopters after all statistical fit index tests have been accounted for. Items with factor loadings over 0.50 are favoured for model preservation. All factor loadings are greater than 0.45, indicating that all variables were retained in the model. This conclusion was in accordance with EFA.

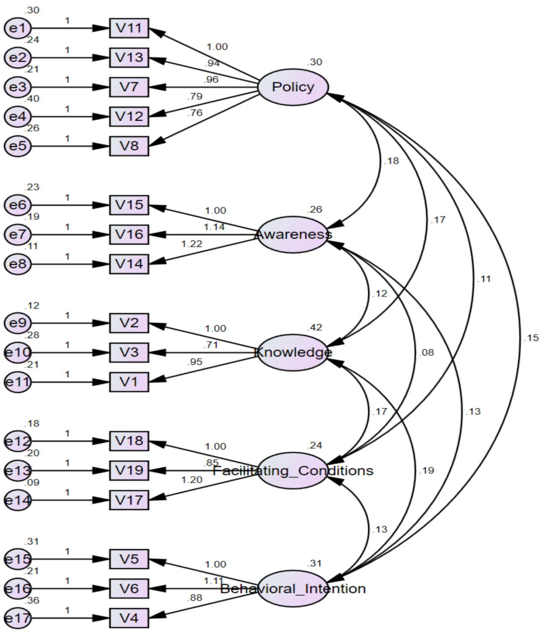

Figure 2 Factor Model for the prospective DT adopters

The number of factors identified from 19 variables, which account for 69.409% of the variation in the acquired data, is likely one of the most significant findings of the present research. The findings of the CFA confirmed the significance of these factors in explaining digital transformation preparation. Although there is no consensus-based line for this number in the scientific literature, it is typically recommended that the amount of variance be high for hypotheses with a solid foundation, moderate for exploratory research, and may be low for uncommon science. This study's major purpose is to evaluate potential digital transformation components; hence, a result of 69.409% may be considered as favorable and moderate. In addition to this, the current study's results have several other implications.

In terms of EFA the development of five factors from 19 variables showed that these factors may be utilized for data summarization, i.e., to explain the complete data set using fewer variables (i.e., 5 latent variables). Therefore, educators and policymakers might concentrate only on these factors with a high degree of abstraction, rather than addressing each variable independently. In addition, interested researchers may extract relevant information from the loading scores (as indicated in Table 5 for future studies, such as retaining only variables with high score loadings for scale creation or using components as summate scores for analysis. The application of the information shown in table 5) is quite subjective since it relies on the analysts' explanation. For instance, analysts of DT might choose one representative variable for each factor to include in their other scales. In this situation, the variable with the highest score may be chosen since it substantially contributes to describing the factor. The highest loading score (0.838) was found for variable 11 ("My workplace has a well-defined DT policy. "), suggesting that it should be kept and used to represent for the other two in Factor 1 (Policy). Similarly, another study may find that V5 ("I have been exposed to DT as part of my training" - 0.814), V2 ("I am comfortable expressing my thoughts when it comes to DT in my expertise" - 0.826), V15 ("I am prepared to adopt DT with the various devices (such as a smartphone, tablet, laptop, and desktop computer)" – 0.862), and V18 ("I anticipate adopting DT within the next twelve months", - 0.852) are useful representations for expressing awareness, knowledge, facilitating conditions, and behavioral intention, respectively. In another research direction, when interested DT researchers prefer to investigate new or unexplained phenomena, variables with low scores (e.g., V8 ("If my coworkers and colleagues are adopting DT, then I should too." – 0.473), V4 ("I am aware of DT through various forms of media promotion" – 0.526) that did not substantially help to describing the factors they belonged would be suitable candidates. As a result, these variables may contribute to other unidentified components, leaving an area of study to be explored. Moreover, cross-loading of a variable may also have beneficial implications. In EFA, as in this research, it is suggested that cross-loading factors be removed (e.g., V9 ("I will embrace DT if it is widespread in my community."), V10 ("My institution has the requisite resources for DT.")). However, this kind of data is important for testing hypotheses, i.e., confirming the interaction between policy and awareness or awareness and knowledge. In this instance, V9 and V10 become crucial elements.

The five-factor model that was uncovered using EFA was then verified by utilizing CFA The results of the CFA analysis provided support for the hidden structure derived from the EFA, meeting all of the acceptable criteria. When discussing how well the CFA model fits the data, it is vital to take into account the criteria of the different model fit indices. According to the findings of several academics, the limited number of participants in the study may have contributed to the issue of low scores. Despite the fact that bigger samples have a stronger influence on certain fit indices than others, scientists estimate that a sample size of 1,600 will produce credible findings for all fit indices (GFI, AGFI, NFI, and RMSEA). However, if the sample size is too big, the statistical power, or the ability to draw conclusions from a small quantity of data, will be reduced. Also, the prior publications found that values in the range of 0.80 to 0.89 are often acceptable. As a result, these values were considered reasonable, and the CFA outputs lends credence to the model in this setting.

Overall, the findings of this research were compatible with those of previous studies (Baabdullah, 2020; Nguyen et al., 2022; Williams et al., 2015), since the questions selected from the literature remained in their components, implying that the conceptual models were still validated in our study context. As a result, these factors might add to the body of knowledge by strengthening the theoretical basis, which in turn facilitates the development of a new theory. Only one notable exception was attributed to questions V7, V8, V9 which were originally derived from the "Social influence" factor. In this study, social influence was merged with policy, implying that these factors were internally correlated. One plausible for this relationship may be explained due to the institution's policy, participants in the national campaign were required to undergo a training course.

The Policy factor in our study reflects the importance of organizational policies and support for digital training programs. This finding is consistent with previous research that has emphasized the need for organizational support in promoting the adoption and success of learning initiatives (Nguyen et al., 2022; Yaakob, 2022). The Awareness factor highlights the importance of raising awareness among participations about the benefits of digital training programs. This finding is consistent with prior research that has identified the need for effective communication (Huong & Duc, 2023). The Knowledge factor in our study suggests that the acquisition of knowledge and skills is a key component of effective digital training programs. This finding is consistent with previous research that has emphasized the importance of providing learners with the necessary knowledge and skills to perform their job tasks (Huong & Duc, 2023; Nguyen et al., 2022). The Facilitating Conditions factor in our study highlights the importance of providing learners with the necessary resources and support to facilitate their learning. This finding is consistent with research that has emphasized the need for adequate technical and instructional support (Alhabeeb & Rowley, 2018). Finally, the Behavioral Intention factor in our study suggests that learners' intentions to apply what they have learned are important predictors of the success of digital training programs. This finding is consistent with previous publications that emphasized the need for learners to apply what they have learned in order to realize the benefits of an IT system (Huong & Duc, 2023; V. T. Nguyen & C. T. Nguyen, 2022; Sun et al., 2008).

Although the present study produced some encouraging results for future adopters of DT, practitioners, and academics, it was constrained by a number of factors. First, only 19 survey items were reviewed and given to participants, thus it is conceivable that more factors were missed. This topic demands greater inquiry since it offers a tight investigative foundation for researchers in this sector. Thus, a literature analysis on the factors that influence DT adopters' views of the need to adopt DT in the future is another intriguing research path that researchers could examine. Second, non-random, purposive sampling method was used in this research, limiting the potential to generalize the findings on a wide scale. Thus, more research is required to verify the selected scales or factors. Third, this study's sample size is restricted to those who participated in the training program; the perspectives of unidentified individuals are not investigated. Thus, future studies should evaluate DT development in further sectors.

CONCLUSION

The purpose of this research was to uncover the underlying factors concealed inside the structure of 19 questions. A total of 318 targeted respondents voluntarily engaged in this study. 159 participants were randomly assigned to EFA, while the remaining 159 samples were held aside for CFA. The EFA experiment indicated that five dimensions accounted for about 69% of the variation in the data, with the remainder attributable to other variables. These latent variables were provisionally designated as policy, awareness, knowledge, facilitating conditions, and behavioral intentions. The CFA results corroborated and validated the five-factor model, with all test measures around the recommended values, suggesting an acceptable fit. These criteria were uncovered in accordance with the suggestions of prior research discovered in the aforementioned literature. Thus, on the one hand, these factors provide educators and policymakers with key areas to discuss as opposed to examining individual indicators, and on the other hand, they serve as a foundation for interested researchers to conduct additional analysis, such as multivariate linear regression or complement for cluster analysis.

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