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Factors affecting the readiness of digital transformation adopters: A case study in Vietnam

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ABSTRACT

In the age of industry 4.0, digital transformation is becoming an increasingly popular term. Prior studies concentrated on advantages and research agenda, but little attempts were made to comprehend and evaluate the postulated conceptual model. Thus, the aim of this research was to understand the latent variables that affected the readiness of digital transformation adopters as well as the importance level between those dimensions. The 12-question survey was designed using Google Form and sent to 97 students of the digital transformation training class. Exploratory factor analysis and multivariate regression were utilized to analyze the obtained survey data. The findings showed that there were 4 main factors affecting the readiness of digital transformation including awareness, facilitating conditions, knowledge and behavioral intention. The total variance extracted by these 4 factors explained 61% of the data variation of 12 observed variables. The results of multivariable regression analysis demonstrated that all extracted factors had an important influence on the readiness of students to transform digitally, in which "behavioral intention" played the most important role. The research results help policy makers and educators have a better overview, thereby making strategies and adjusting plans according to the priority level around the above 4 factors. It also serves as a basis for other in-depth studies, and as a reference for interested digital transformation readers.

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INTRODUCTION

In recent years, "digital transformation" has garnered considerable attention (Geroche & Yang, 2022; Vinh T. Nguyen & Chuyen T. H. Nguyen, 2022; Noceto, 2022; Silva et al., 2022). This concept may be found in several industries, including education (Aditya et al., 2021; Benavides et al., 2020; Bogdandy et al., 2020; Oliveira & de SOUZA, 2022), finance (Heavin & Power, 2018; Safeena et al., 2011), culture (Jung et al., 2020; Yoo et al., 2020), as well as public administration (Rot et al., 2020; Scupola, 2018). In the 1940s, Claude Shannon lay the groundwork for the digitalization of information, marking the beginning of the era of digital transformation (Schallmo & Williams, 2018). The invention of microchips and transistors in 1950 marked the beginning of the digital revolution, when analog signals were turned to digital signals. This revolution is exemplified by instant messaging, computers, the Internet, and personal computers (Benavides et al., 2020; Reis et al., 2018; Schallmo et al., 2017). According to several research, the phrase "digital transformation" was coined by the consulting firm Capgemini and the MIT Center for Digital Business in late 2011 to describe the use of technology to dramatically increase the performance or reach of a company. The first success of the digital transformation project occurred in 2014, and since then, it has extended to a variety of industries and nations (Reis et al., 2018; Schallmo et al., 2017).

It may be claimed that the digital transformation process has been silently occurring for many years, and Covid-19 is the agent that speeds up the digital transformation process (McAuliffe et al., 2021; Nguyen, 2022; Vinh T. Nguyen & Chuyen T.H. Nguyen, 2022; Srisathan & Naruetharadhol, 2022). While some industrialized nations have taken advantage of their strengths in resources, infrastructure, and technology to become leaders in this sector, others are still stumbling (Silva et al., 2022). Vietnam, for example, is one of the countries that excels in outsourcing software and internet systems but ranks quite poorly worldwide and regionally in terms of digital transformation (Cameron et al., 2019). Faced with this challenge, the Vietnamese government has devised a comprehensive road map for digital transformation to 2025, with a vision to 2030, through a range of policies and initiatives. The creation of the national digital conversion date (10 October of each year, pursuant Decision No. 505/QD-TTg) is one example (Van LAM, 2021).

However, during the process implementation, there are still a great number of obstacles and problems that must be overcome in order to achieve effective digital transformation (Cameron et al., 2019; Van LAM, 2021). Some obstacles include a lack of infrastructure, inconsistent internet, insufficient digitization support tools, poor learner awareness, understanding of digital transformation, and digital transformation capabilities (Auer & Tsiatsos, 2018; Henriette et al., 2016). Thus, the overarching questions are 1) what are the most influential factors in digital transformation readiness? 2) How crucial are these factors?

Numerous scientific studies have been conducted on the problems and factors regarding digital transformation globally. For instance, Jović et al. (2022) examined and validated the effects of organization, technology, digitalization, and environment factors on digital transformation direct and indirectly in maritime transport sector. By adopting the Technology-Organizational-Environmental (TOE) framework, Daniels and Jokonya (2020) found that technological factor seemed to have more influential on digital transformation in the retail supply change compared to the other two factors (i.e., organization and environment). Laorach and Tuamsuk (2022) conducted an experiment with administrators in university settings, their results reported that digital culture, digital strategies, management process, organization leaders, digital technologies, and staff were six important factors influencing digital transformation adoption. In telecom industry, Aghayari et al. (2022) also identified six factors with respect to the success of digital transformation (i.e., government, business model, culture, technology and workforce) and that government played the highest role among others. Tungpantong et al. (2021) utilized the DeLone and McLean model with respect to digital transformation in higher education institutions, their results revealed that 18 variables could be grouped in three factors namely as digital transformation (6 variables), enterprise architecture (5 variables), and digital leadership (7 variables). Dery et al. (2017) emphasized that awareness played a vital role in digital transformation as it would express a positive attitude towards change and technology. Tripathi and Urkude (2022) found that task-technology fit and facilitating conditions were the two factors that influenced instructors' performance on digital transformation. Oliveira and de SOUZA (2022) highlighted that knowledge, skills and attitudes were important factors in sustaining education in the era of digital 4.0.

It can be seen from the previous selected publications that there were numerous factors affecting the success of digital transformation. Thus, it is infeasible to examine all of them in a single study. In this regard, the current research examined whether previous studied factors are still applicable in the context of our current study setting, that is, awareness, facilitating conditions, knowledge, and behavioral intention.

OBJECTIVES OF THE STUDY

The objective of this research is to determine the factors that influence digital transformation readiness and the relative importance of those components.

MATERIALS AND METHODS

Participants

The participants in this study were prospective adopters of digital transformation working in universities and public administration offices as part of a government training program from May to December 2022. After each training session was finished, Google Form was used to administer the survey to participants. Respondents were informed of why data were gathered and how it would be utilized prior to consenting to its collection. Participants were permitted to respond or exit the survey at their discretion. IRB was not required since no personally identifiable information was obtained.

There was a total of sixteen questions on the survey, four of which were designed to collect demographic data (such as respondents' ages, genders, and primary occupations) and another twelve to probe more deeply into the context of digital transformation. Because people choose whether to take part in the training, it is more effective to collect data using a non-probabilistic, purposive sampling technique. Participants were asked to indicate how much they agreed or disagreed with each statement using the Likert scale (Totally Disagree (1), Disagree (2), Neutral (3), Agree (4), Completely Agree (5)). The questionnaires were adapted from previous studies (Balbo Di Vinadio et al., 2022; Williams et al., 2015) and rationalized to fit with our study context.

The information presented in Table 1 pertains to the study's participants. 44 males represented 45.36 percent of the sample, while women made up more than half (54.64 percent). There were only four students in the class between the ages of 18 and 25 and seven students over 45. The remainder are between the ages of 26 and 45, with 55.67 percent between the ages of 26 and 35 and 32.99 percent between 36 and 45. More over half of the survey participants are employed in the sector of education (53.61%), while the remainder are employed in the field of public administration (46.31%). The majority of participants have a master's degree (57.73%), followed by a university (39.18%), and just three persons have a PhD/doctorate degree (3.09%), as shown in Table 1. Literature research (Hair, 2009; Tabachnick et al., 2007) yielded a number of suggestions about sample size, each of which examined the data from a unique viewpoint. For instance, 100 or more samples would be desirable in the majority of studies, or a 5:1 ratio indicating that there should be at least five times as many observations as variables. In our research, the ratio of observations to variables is 97:12, or 8:1, indicating that the sample size is sufficient for data analysis.

Table 1. General information about respondents (N = 97)

Variable	Item	Freq	Percent
Gender	Male	44	45.36
	Female	53	54.64
Age	18-25	4	4.12

	26-35	54	55.67
	36-45	32	32.99
	Over 45	7	7.22
Working Sector	Education	52	53.61
	Public Administration	45	46.39
Education	Bachelor	38	39.18
	Master	56	57.73
	PhD	3	3.09

Research Method and Design

To answer question 1), what are the most influential factors in digital transformation readiness? Methodologically, exploratory factor analysis (EFA) was utilized (Hair, 2009). This is a statistical approach for reducing a large collection of interdependent variables into a smaller number of variables (called factors) that are more important while retaining most of the original contents. It helps scientists to create new hypotheses or models based on a large array of evidence. A central tenet of EFA is the common factor model, which states that all indices may be expressed as a linear combination of some fixed number of common indices and a single factor (Hair, 2009). Common factors are thought to be hidden, unobservable entities that influence several indicators in a collection and explain for correlations between indicators. The latent variables are believed to influence only one of a set of indicators and do not explain for the association between the indices. By constructing relationship models between the indices and indexed latent components known as factor loads, the common factor model attempts to explain the correlation pattern of the indices. In the absence of a theoretical basis for determining the number and pattern of common latent components, EFA is ideally suited for scaling. The applications of EFA were investigated in a number comparable studies (Dinh et al., 2022; Nguyen et al., 2022)

To investigate the second study question, i.e., how significant are these factors? The data was analysed using a multivariate linear regression (Hair, 2009). Following the completion of exploratory factor analysis, the eigenvalue-possessing factors were employed as independent variables in a further round of multivariate regression. The method's intention is to measure the degree of association between the most influential factors in digital transformation adoption. Multivariate linear regression has been utilized to address the similar research questions in many prior publications (Cruz et al., 2022; Go, 2022)

Research Tool

For this study, we utilized RStudio, a program for statistical analysis (Luo et al., 2019). RStudio is mostly used with the computer language R, while it also supports a wide variety of other languages. As a means of aiding in programming, psych and mentalTools libraries are used (Luo et al., 2019). R is more complicated than SPSS since it needs data analysts to learn programming, but it's free and offers a lot of extra tools that SPSS doesn't provide (such as multi-language, building statistical website in R,...).

RESULTS AND DISCUSSION

Exploratory factor analysis

Before exploratory factor analysis (EFA) was undertaken, the data's adequacy for factor analysis was assessed using the Kaiser-Meyer-Olkin (KMO) scale (Hair, 2009). Using this method, we can assess the sample adequacy not just for individual model variables, but for the whole model as a whole. KMO levels greater than 0.5 are generally considered sufficient for EFA (Hair, 2009). For factor analysis, it is required to evaluate if there is a sufficiently high correlation between questionnaires; this is performed using the Bartlett test. The test findings of Bartlett are only included if they are statistically significant (sig. 0.05).

Table 2 shows that the KMO value is 0.68 which is more than the required 0.5 (Hair, 2009). Furthermore, the result of Bartlett's test of sphericity is $\chi 2$ (66) = 376.4162, $\rho < 0.000$, suggesting that the correlations among the items in the questionnaire are sufficient to undertake EFA (Hair, 2009).

Table 2. Measurement for KMO and Bartlett test

Kaiser-Meyer-Olkin Factor Adequacy		0.68
Bartlett's test	chisq	376.4162
	p.value	5.139115e-45 (< 0.000)
	df	66

The parallel analysis scree plot is shown in Fig. 1. The information on the figure implies that the exploratory factor analysis experiments yielded 4 factors and 3 components (Hayton et al., 2004). Based on the figure, the optimal solution involves four components since no triangle is on the black line (the eigenvalue line). Similarly, these four variables are located on the FA Simulated Data curve (see Fig. 1).

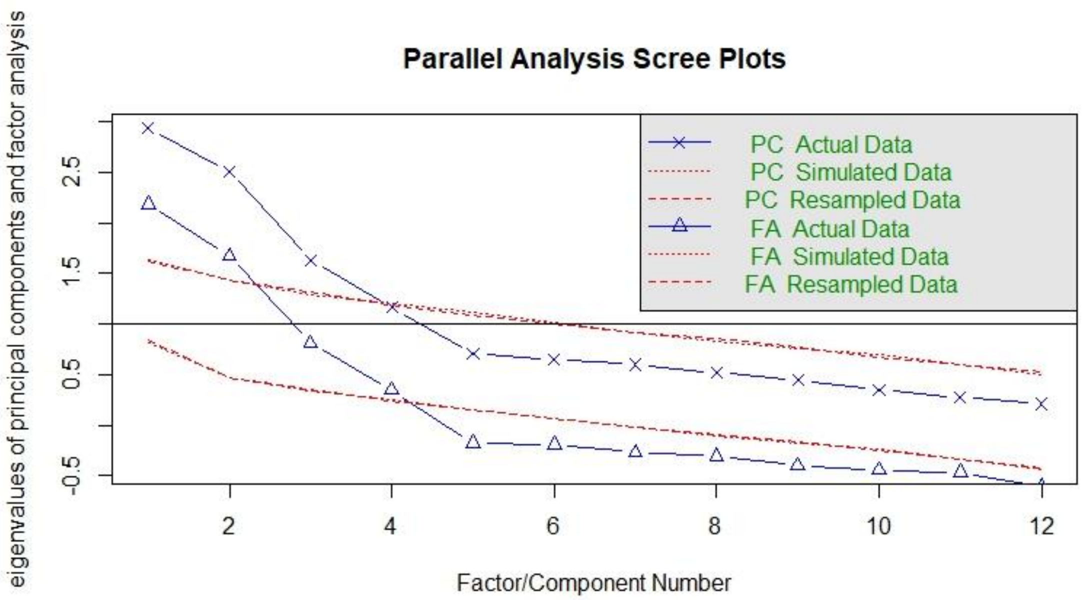

Fig. 1 Parallel Analysis Scree Plots

The loading coefficients of the variables (questions) for each factor are shown in Table 3. With a sample size of around 100, Hair (2009) states that a load factor larger than 0.55 is statistically significant. According to Table 3, the variable V9 should be evaluated for exclusion from the questionnaire (since it has a value less than 0.55). Moreover, examining the variable V4 reveals that it has a cross-load in both Factor 3 and Factor 4, therefore it must also be discarded. Complexity indicates how clearly a variable is associated with a factor. The complexity will be optimal when the variable values are less than 1.5 (Luo et al., 2019). Similarly, variables V4 and V9 do not obviously correspond to only single factor.

Table 3. Factor loadings and complexity

	Factor 1	Factor 2	Factor 3	Factor 4	Complexity
V1	0.88				1.2
V2	0.94				1.0
V3	0.68				1.3

V4		0.56	0.50	2.2
V5		0.89		1.2
V6		0.59		1.3
V7			0.65	1.1
V8			0.62	1.3
V9			0.52	1.5
V10	0.83			1.1
V11	0.84			1.1
V12	0.68			1.1

The data in Table 4 include the sum of the load squares (SS Loadings), the percentage of variance (Proportion Var), the sum of the cumulative percentages of variance (the Cumulative Var), the percentage of variance explained (Proportion Explained), and the total cumulative proportion (Cumulative Proportion). Eigenvalues are the total of load squares. When using the correlation matrix, the total number of factors will equal the number of variables included in the study. According to Hair (2009), for analysis, only factors with eigenvalues greater than 1 are retained. Table 4 demonstrates that all four variables have values greater than 1. The ratio of variance indicates that factor 1 explains 19% of the data, factor 2 explains 17%, and factors 3 and 4 explain 13%. The cumulative sum of the four aforementioned elements is 61%, or, to put it another way, these 12 questions account for 61% of the significance of factors impacting digital transformation readiness, while the remaining 39% is attributable to other factors.

Table 4. Loadings and Variance

	Factor 1	Factor 2	Factor 3	Factor 4
SS Loadings	2.24	2.00	1.60	1.51
Proportion Var	0.19	0.17	0.13	0.13
Cumulative Var	0.19	0.35	0.49	0.61
Proportion Explained	0.30	0.27	0.22	0.21
Cumulative Proportion	0.30	0.58	0.79	1.00

Labeling factors: According to Hair (2009), factors with the highest loading coefficients should be given priority names in the labeling of factors. The four latent components are thus designated as follows. The first factor is titled “Awareness,” the second is “Facilitating Conditions,” the third is “Knowledge,” and the fourth is “Behavioral Intention”. The questions and their corresponding criteria are provided in Table 5.

Table 5. Labelling, structure, reliability and loadings of factors

Variable	Items	Loadings
Factor 1: Awareness (Cronbach’s alpha α = 0.816)		
V1	I understand the meaning of digital transformation	0.88
V2	I am aware of how digital transformation applies to my work environment.	0.94
V3	Before attending this workshop, I had heard about digital transformation.	0.68
Factor 2: Facilitating Conditions (Cronbach’s alpha α = 0.706)		
V4	The agency I work for has adequate infrastructure for digital transformation	0.56
V5	The agency I work for has adequate human resources for digital transformation	0.89
V6	The agency I work for has full tools, software and services to perform digital transformation	0.59
Factor 3: Knowledge (Cronbach’s alpha α = 0.613)		
V7	The amount of knowledge in the digital transformation awareness class is easy for me to understand	0.65

V8	The content of digital transformation in the training program is suitable for me	0.62
V9	The materials provided in the training program are sufficient for me.	0.52
Factor 4: Behavioral Intention (Cronbach's alpha α = 0.821)		
V10	I plan to take my next digital transformation training program	0.83
V11	I am ready to apply the digital transformation within the next 6 months	0.84
V12	I am prepared for digital transformation within the next 12 months.	0.68

Multivariate Linear Regression Analysis

According to the results of a multivariate regression study, the above four factors account for 96% of the variance in digital transformation readiness ($F (4.62) = 517.6$, $p < 2e\text{-}16$), with $R^2 = 0.969$. The summary of the independent variables and their respective parameters for the multivariate regression model are shown in Table 6. The results revealed that all extracted factors significantly affected students' digital transformation readiness ($p < 0.000$), with "Behavioral Intention" having the greatest impact.

Table 6. Summary of the multivariate regression model

Coefficients	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	38.1435	0.1261	302.45	<2e-16
Awareness	2.2748	0.1260	18.06	<2e-16
Facilitating Conditions	3.3489	0.1344	24.92	<2e-16
Knowledge	2.2575	0.1355	16.66	<2e-16
Behavioral Intention	3.7814	0.1494	25.32	<2e-16

Variance inflation factor (VIF) values for each component are as follows: Awareness (1.003687), Facilitation conditions (1.022989), Knowledge (1.004543), and Behavioral Intention (1.003687). VIF is a measure used to assess the phenomenon of collinearity in regression models (Craney & Surles, 2002; Hair, 2009). The lower the VIF, the less probable multicollinearity is to occur. Hair (2009) indicated that a VIF threshold of 10 or above would exhibit robust multicollinearity. VIF should be maintained as low as feasible, since multicollinearity may exist even at VIF values of 5 or 3. In the current research, the VIF coefficients of the independent variables are all less than 2, hence the results do not contradict the multicollinearity assumption. From the regression coefficients, the unnormalized regression model is constructed as follows:

Digital transformation readiness = 38.1435 + 2.2748 * (Awareness) + 3.3489 * (Facilitating Conditions) + 2.2575* (Knowledge) + 3.7814* (Behavioral intention).

Discussion

Perhaps, one of the most notable findings in the current study is the number of factors extracted from 12 variables and these factors account for 61% amount of variance in the obtained data. Multivariate linear regression results provided promising outputs that confirmed the significance of these factors in explaining digital transformation readiness. Although there is no consensus-based line for this number in the literature, it is usually recommended that the amount of variation should be high for solid ground theory, mediate for exploratory research, and may be low for rare science. The main purpose of this research is to explore dimensions of emerging digital transformation, thus 61% could be considered as promising and mediate result. In addition to this, there are several implications drawn from the results of the current investigation.

In terms of exploratory factor analysis, the formation of four factors from 12 variables indicated that these factors can be used as data summarization, that is, to describe the entire data set with fewer variables (i.e., 4 latent variables). As such, managers and policymakers could focus only on these high level of abstraction variables rather than dealing with each variable separately. Furthermore, interested researchers can extract useful information from the loading scores (as shown in Table 3) in their future studies such as keeping only these variables with high score loadings for the scale development or use factors as summate score for analysis. The use of information provided in Table 3 is quite subjective because it depends on the justification of the analysts. For example, digital transformation analysts can select one representative variable on each factor to incorporate with their other scales. Such in this case, the variable with high score may be preferable because it contributes significantly to explaining its factor. Experimental results from this study revealed that variable 2 ("I am aware of how digital transformation applies to my work environment") could be extracted because its loading score is the highest (0.94) and it could represent for the other two in factor 1 (awareness). Similarly, V5 ("The agency I work for has adequate human resources for digital transformation" - 0.89), V7 ("The amount of knowledge in the digital transformation awareness class is easy for me to understand" - 0.65), V11 ("I am ready to apply the digital transformation within the next 6 months" - 0.84) could also be used in another research for representing facilitating conditions, knowledge, and behavioral intention respectively. In another line of research when interested digital transformation analysts want to explore new or unexplained phenomenon, variables with low scores would be good candidates (e.g., V4 ("The agency I work for has adequate infrastructure for digital transformation" – 0.56), V6 ("The agency I work for has full tools, software and services to perform digital transformation" – 0.59), V9 ("The materials provided in the training program are sufficient for me" – 0.52)) since they did not contribute significantly in explaining factors they belong to. As such, these variables can contribute to other factors that have not revealed, leaving a research gap for investigation. In another research direction, cross-loading of a variable could also carry useful implication. In exploratory factor analysis as in this study, it is recommended that variables with cross-loading should be excluded (e.g., V4 ("The agency I work for has adequate infrastructure for digital transformation" which had a loading of 0.56 on knowledge and a loading of 0.50 on behavioral intention). However, this kind of information become variable in hypothesis testing, that is, to validate the relationship between knowledge and behavioral intention. In this case, V4 becomes an important variable.

Examining Cronbach's alpha in Table 5 showed that, of the four factors (i.e., awareness, facilitating conditions, knowledge, behavioral intention), the Cronbach's alpha of knowledge is quite low compared to other factors and to the normal recommended threshold (0.7). The low score of Cronbach's alpha on knowledge indicated a lack of consistency in rating item scales of participants who took part in the digital transformation training program. What that means is that the amount of knowledge, the content of digital transformation and materials provided are fairly intercorrelated. One plausible explanation for these relationships is that respondents come different sectors (i.e., universities, public administration), at various ages, and heterogeneous levels of education. As such, they would have different viewpoints in answering each question. For example, participants from universities may have prior knowledge on digital transformation but they found content and materials provided are not sufficient to strengthen their knowledge. On the other hand, respondents from public administration may have little prior knowledge on digital transformation, thus content and materials may be considered adequate but not easy to understand. This result provided implication for policymakers and educators that personalized training should be considered to increase the national training program performance. In this regard, adaptive learning with the help of artificial intelligence should be considered in the future.

In terms of multivariate linear regression, the equation formed from 4 extracted factors may provide interested readers with three interpretations. First, it may be used as data summation, that is, to describe four factors (or 12 variables) from 97 observations in a single formula. Second, it provides a mechanism to predict digital transformation readiness based on these four factors. As such, policymakers can rely on this equation to examine the level of digital transformation readiness for a particular agency. The use of multivariate linear regression for prediction is paramount of importance in the context of national strategies as it allows decision makers to adjust their policies at large scale. Third, the weights on the regression model may also aid managers to prioritize on which factor first when improving all factors are not applicable. In this study, behavioral intention, or the willingness to change in the future plays the most vital role, followed by facilitating conditions, awareness and knowledge. This implies that educating citizens about changes is up most crucial for the success of the national strategies. Only when citizens accept changes from their mind, other approaches may become feasible such as facilities and education.

Compared to previous studies in which we adapted the factors and questionnaires (Balbo Di Vinadio et al., 2022; Williams et al., 2015), our experimental results yielded comparable findings. What that means is that variables remain in their respective components, indicating a high degree of internal correlation. On the other hand, in contrast to previous research, several variables, such as V4 and V9, did not exhibit strong factor loadings, which may suggest that there is some amount of heterogeneity across the samples in studies.

This study encountered some limitations as follows. Firstly, only 12 variables were included in the analysis. Therefore, data still need to be collected in subsequent training courses to discover more latent variables. Second, the method of confirmatory factor analysis (Confirmatory Factor Analysis) was not tested in this study. The study will be more complete if the number of samples is large enough, then half of the samples will be analyzed through EFA to find out the main factors and structure of those factors and the rest will be through CFA. When the factors found in the EFA method are tested through the CFA method, the confirmation of the number of factors in the data will be enhanced rather than depending on a single method.

Based on the findings and limitations above, there are several potential research directions that could be of interest for researchers. First, prospective researchers can replicate the current study in their settings to examine whether their results could support these findings. The confirmation of the results could support in creating a new model in terms of digital transformation or constructing a new theory. Second, it is called to utilize different statistical methods to look at data from different angles. In this regard, findings would contribute to have better understand of users' behavior with respect to digital transformation. Third, more items or survey questions could be added to explore other potential factors that have not investigated in this study. The results could help to explain cross-loading scores more clearly.

CONCLUSION AND RECOMMENDATION

The purpose of this research is to determine the factors influencing prospective adopters' readiness for digital transformation while also assessing the significance of the factors. According to the findings of exploratory factor analysis, there are four critical components influencing digital transformation readiness namely as: awareness, facilitating conditions, knowledge, and behavioral intention. The overall variance extracted by these four components is 61%, implying that the four extracted factors explain 61% of the data variation of 12 observed variables, with the remaining 39% attributed to other factors. The findings of multivariable regression analysis demonstrate that all obtained factors have a significant impact on adopters' readiness to change digitally, with "behavioral intention" playing the most crucial effect. The study findings provide policymakers and educators with a better picture, allowing them to devise policies based on the priority level of the aforementioned four factors rather than needing to examine them directly. It also serves as a foundation for further research and as a reference for interested readers.

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