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The Perceptions of Prospective Digital Transformation Adopters: An Extended Diffusion of Innovations Theory

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***Abstract* – This study investigated the effects of factors that influence users' perceptions to adopt digital transformation. Eight hypotheses were proposed and tested employing the Structural Equation Modeling. 248 government personnel, instructors, and students were recruited to answer the questionnaires through Google Form. The experimental results indicated that facilitating conditions, policy, social influence, and knowledge all had a positive and significant impact on digital transformation adoption. Meanwhile, policy was found to have a positive effect on social influence. In turn, social influence positively affected knowledge. In addition, awareness was verified to be a reliable predictor of knowledge. The notable exception was that the awareness factor was shown to have no effect on digital transformation adoption. Thus, traditional reaching to citizens via television, news, broadcast needed to re-examined. Overall, the model accounts for 52.5 percentage of the variation in the data. Four recommendations were proposed for practitioners, and limitations were roughly discussed. Future study is needed to re-examine the unexpected effect of awareness on digital transformation adoption.**

***Keywords* – digital transformation, awareness, technology, research-based, factor analysis.**

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1. Introduction

Digital transformation (DT) is a phrase that is gaining a lot of attention in recent years [1], [2]. Its influence and presence appear in all areas of life, from economy, culture, politics to tourism, entertainment and education [3], [4]. The history of digital transformation can be dated back to the 1940s when Claude Shannon laid the foundation for the digitization of information through his research on the mathematical theory of communication [5]. Only a few years later (1950s), microchips and transistors were invented, marking the era of the digital revolution - when analog signals were converted to digital signals. Classic examples of this revolution include instant messaging, microcomputers, the internet, and personal computers [1], [2], [6]. According to many research [2], [7], [8], the term “digital transformation” was first coined by the consulting firm Capgemini, in collaboration with the MIT Center for Digital Business in late 2011 to refer to the use of technology that radically improve the performance or reach in the business. 2014 was the year that marked the first success of the digital transformation project and since then, the spread of this successful project has spread to many different fields [1], [8], [9]

It can be said that each industry and field has different modes of operation and success evaluation criteria. Therefore, the term digital transformation is also recognized and defined in many ways [10], [11]. For example, in the systematic review of digital transformation, Vial [2] showed that there were at least 23 unique definitions of digital transformation. More specifically, in the corporate sector, digital transformation is understood as the use of technology to radically improve the performance or reach of a business, affecting all aspects of customers' lives [12]. In terms of technical perspective, it is understood as an organizational shift to big data, analytics, cloud, mobile and social media platforms [2]. Some other authors see digital transformation as a social phenomenon, or a cultural revolution where people still play the role of subjects rather than machines and devices.

The views above show that it is challenging to give a common definition for everyone. In the authors' opinion in this article, digital transformation is understood as the conversion of properties and methods of an object to another way in which digitized data is present. Accordingly, objects can be understood in many different ways, can be people or organizations, can be tangible or intangible. Properties are descriptions of objects, and methods are actions, activities, and behaviors.

In the academic field, there is a wide range of scientific publications publishing articles related to digital transformation and its impact on different fields and industries [13], [14]. Prominent among these areas are medical, computer science and engineering. The cause of this phenomenon can be explained directly that the activity of the above fields is associated with digital tools, while in other areas the presence of digital tools only plays a certain role [6], [9]. For example, group discussion, cultural understanding or social interaction are the types of activities that indicate the presence of little or no technological devices. However, since the Covid pandemic appeared, these activities can hardly be maintained without the support of technology due to social distancing [7], [13], [15], [16]

It is knowledgeable that digital transformation has been quietly happening for many years and that Covid-19 is the agent that makes the process of digital transformation happen faster [17], [18]. While some developed countries have taken advantage of their strengths in resources, infrastructure and technology to pioneer in this field, others are struggling to find their way [19]. For example, Vietnam is one of the countries with strengths in software outsourcing and exporting, and the internet system, but ranks in a rather low position in the world in terms of digital transformation, even within its region [20]. Faced with that problem, the Vietnamese government has built a comprehensive digital transformation road-map to 2025, with a vision to 2030 [21]. Many policies have been put in place, a number of massive training programs on digital transformation have been implemented to citizens at a varying degrees [21]. However, as being in charge of the implementation process, many challenges and difficulties have to be solved such as inequality in technology, people's awareness, knowledge about digital transformation, social influence, or specific policies for each sector [7], [22]. In this regard, there are many different variables that affect the success of digital transformation, and addressing all of them simultaneously requires effort and time. Therefore, the aim of this research is to better comprehend the latent variables that affect users' behavior to adopt digital transformation.

In other words, the authors aim to examine a proposed model considering various technological and social-related variables that influence users' behavioral intention. The results of this study will be the basis for policy maker to justify their decision making. At the same time, it also serves as a reference for researchers in countries with similar socio-economic similarities.

2. Theoretical frameworks

As indicated in the preceding section, the terminology "*digital transformation*" is interpreted from a variety of perspectives, thus there are several ways to apply it to specific situations [2], [6], [8]. However, regardless of the perspective, transformation is required, from human behavior, operational procedures to infrastructure. To understand and explain the changes in general, many theoretical models have been proposed and widely applied. Some examples include Theory of Reasoned Action [23] - seeks to clarify the interaction of actions and attitudes in human behavior; Diffusion of Innovations Theory [24]- seeks to explain how emerging discoveries will be adopted societies and civilizations, from introduction to widespread use; Theory of Planned Behavior [25]- was developed in response to the Theory of Reasoned Action's constraint that human action is totally controlled by reason; Stimulus Response Theory [26] - tries to explain that people's behaviors were affected by their knowledge; Technology Acceptance Model [27] seeks to explain that the adoption of an IT system was influenced by its usefulness and ease of use; or the Unified Theory of Acceptance and Use of Technology models [28] - unifies eight prior models; and their variations.

Currently, there is still no consensus on which theoretical model to choose, because each model will look at the same phenomenon from different angles. As a result, in this study, the authors construct a theoretical model based on the core idea from the Diffusion of Innovations Theory model combined with other factors deemed significant for the early stages of digital transformation in Vietnam.

Behavioral Intention: This term is defined as the likelihood in the individual's willingness to adopt a new thing. Here, thing can be understood as tangible or intangible products. For example, authors in [27], [28] considered thing as an IT system. On the other hand, thing is understood as the culture in the study of Pagliaro et al. [29]. In this study, thing refers to the likelihood that citizens are willing to adopt digital transformation in their work and life.

Knowledge: The knowledge factor refers to the expertise required to identify, comprehend, and develop new technologies [30].

In the Knowledge-attitude-behaviour model, Kallgren and Wendy Wood [31] showed that users would have positive or negative attitudes toward using a system depending on the level of knowledge they acquired. In the current research, knowledge refers to a belief that if an individual had an understanding of digital transformation, he is likely to adopt digital transformation in the near future. Dhir et al. [32] reported that knowledge is a predictor of user behavior, thus the following tentative assumption was developed:

Hypothesis 1. Knowledge will positively affect Digital Transformation Adoption

Awareness of Digital Transformation: Ajzen [25] conceptualized perceived awareness as the level of knowledge that something exists or understanding of a subject based on experience/information in order to learn the features of an IT system. This factor has been investigated in a number of studies and their experimental results indicated that awareness is a predictor of behavior intention toward utilizing an IT system [33, 34]. Here, in the context of this research, awareness refers to the likelihood that citizens are informed about digital transformation through a variety of channels, thus gaining knowledge and understanding of the digital transformation. Based on the previous findings on the effect of awareness factor of behavioral intention, the following hypotheses were proposed:

Hypothesis 2. Awareness of Digital Transformation will have positive impact on Digital Transformation Adoption

Hypothesis 3. Awareness of Digital Transformation will have positive impact on Knowledge

Social Influence: Social influence refers to both purposeful and involuntary efforts to alter another person's views, attitudes, or behaviour. Venkatesh [28] reported that social influence had a positive effect on behavioral intention. In addition, Watjatrakul [35] reported that this factor influenced individual knowledge. In the current study, social influence implies colleagues and friends that would change one's intention to adopt digital transformation and willingness to enhance one's knowledge. As such, the following hypotheses were created:

Hypothesis 4. Social influence will impact Digital Transformation Adoption positively

Hypothesis 5. Social influence will have positive impact on Knowledge

Facilitating Conditions: Venkatesh [28] considered this factor as a belief that users are willing to adopt a new technology if they have infrastructures or facilities required to operate an IT system.

This factor has been widely used in the literature [28], [36], especially in the domain related to information technology [37]. Here, in this research, facilitating conditions refer to the degree at which individual has devices/facilities to perform digital transformation. Venkatesh [28] reported that facilitating conditions had a positive influence on behavioral intention, thereafter the following assumption was made:

Hypothesis 6. Facilitating Conditions will have positive impact on Digital Transformation Adoption

Policy: This factor refers to a set of protocol and procedures to follow within an organization or institution [38], [39]. Yang et al. [39] reported that policy played a crucial role in prefabricated digital transformation of innovative ecosystem. In this study, policy implies statements, protocols designed to get users involved in the digital transformation. If the policy is clear, users are willing to adopt digital transformation and they will encourage others to adapt with the changes. Thus, the following hypotheses were proposed:

Hypothesis 7. Policy will have positive impact on Digital Transformation Adoption

Hypothesis 8. Policy will have positive impact on Social Influence

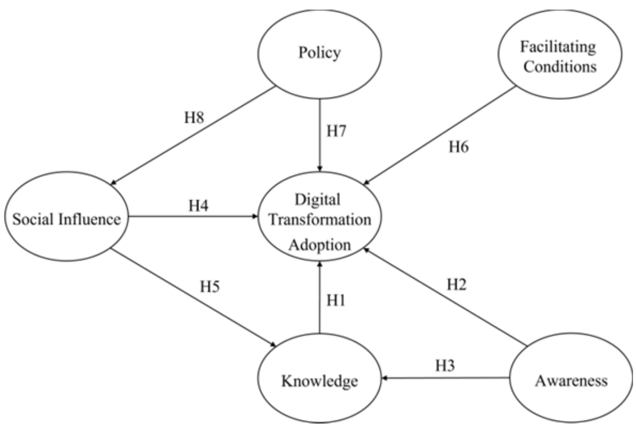

Figure 1 The proposed conceptual framework investigates factors influencing digital transformation adoption.

Figure *1* depicts the proposed conceptual model based on the hypotheses. Each factor is represented by an oval, and the hypothesis is denoted by an arrow.

3. Materials and Methods

In the following sections, we detail the data collection, measurement, and analysis processes so that interested researchers can replicate the study in their own settings.

3.1. Data Collection

Following a digital transformation road-map of the Vietnamese government, a large number of training programs for educating digital citizens has been implemented across the sectors. Thus, the target population or subjects of interest are individuals who participate in this large-scale training program. It comprises students, professors, and government personnel who will be in charge of information management at their respective institutions/organizations. Due to the selective participants involved in the training, the non-probability, purposive sampling strategy is preferred for data collection. After completing the course, participants were invited to take part in a brief survey. Google Form was used to present a set of questionnaires that consists of two parts: 1) Four questions about general information of the participants, and 2) 19 questions about their thoughts on digital transformation adoption. The link to the survey was shared on the class discussion thread. Data was collected from 5/2022 to 10/2022. In addition to the survey, short conversations and discussions with participants during class sessions were recorded.

There are various discussions in the literature concerning the appropriate sample size necessary for undertaking analysis. The sample size may be as low as 100 observations to 500 or even 1000 samples, depending on the problem posed. For example, Anderson [39] claim that 100 samples are enough for the algorithms to converge while Kline [40] recommend that this number should be maintained at least from 100 to 200 subjects per study and an appropriate number is from 300 to 500. Another approach is based on the ratio between free parameters and samples in which the ratio of 1:5 (one free parameter needs five samples) is considered as low, 1:10 is considered as intermediate, and 1:20 is an ideal case [40]. Sober [41] provided a free web-based tool to estimate the minimum sample size based on some statistical criteria such as effect size, statistical power, number of latent variables, and probability level. The current study used the tool to estimate the sample size, and it yielded a result of at least 177 observations.

3.2. Measures

This present study used a five-point Likert scale to assess how much each participant agreed with the statement in each question. In this regard, one represents strongly disagree with the statement whereas five denotes strongly agree. Similarly, two, three, and four represent disagree, neutral, and agree respectively. *Table 1* provides a specification of the construct and its indicators.

Table 1 Construct and Indicators

Code	Indicators
	Knowledge of Digital Transformation (KD) [38]
KD1	I think I have knowledge for DT
KD2	I feel confident when talking about DT in my field
KD3	I think I understand DT in a given context
KD4	I can think of some strategies to foster DT at my institution or organization
	Awareness of Digital Transformation (AW) [40]
AW1	I am informed of DT through a variety of advertising channels
AW2	I am informed of DT through a training program
AW3	I am informed of DT through my institution/organization`s policy
	Social Influence (SI) [28]
SI1	My colleagues/friends think that I should adopt DT
SI2	I think I will adopt DT if my colleagues/friends are adopting it
SI3	I will adopt DT if it is being widely adopted in my community
	Policy (PO) [38]
PO1	My institution/organization has a clear policy for DT
PO2	The policy for DT is easy to follow
PO3	I can adjust myself to follow the policy
	Facilitating Conditions (FC) [28]
FC1	My institution/organization has the resources necessary for DT
FC2	I have the devices (e.g., smartphone, tablet, laptop/desktop) ready for DT
FC3	If I have an issue related to DT, I can get support from IT department/service providers
	Digital Transformation Adoption (DTA) [28]
DTA1	I intend to adopt DT in the next 6 months
DTA2	I predict that I have to adopt DT in the next 12 months
DTA3	I plan to adopt DT whenever I have a chance to do it

3.3. Data Analysis

Figure 1 showed that there are complex interactions among factors, both direct and indirect effects. Conventional multivariate data analysis techniques (e.g. multiple linear regression) had some issues as they cannot solve the equations simultaneously [41]. In this regard, Structural Equation Modeling (SEM) is a preferable method employed in this current study as it allows to overcome the traditional techniques [41]. In SEM, there are two methods typically used by researchers, including covariance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM).

While the former is used largely to validate theories, which requires a large sample size and a normal distribution, the latter is commonly used for developing theories and prediction in the model estimations, which relaxes the rigorous normal distribution assumption. Since the current research employed non-probability and purposive sampling strategy, the normal distribution is not warranted. Thus, PLS-SEM approach was selected in the study design. Of the many techniques available for PLS-SEM [41], [42], the authors utilized the Generalized Structured Component Analysis (GSCA) due to its flexibility to work with even small samples [43], [44]. GSCA has been applied in various domains [37], [38], [45]. GSCA Pro 1.1 [46] was used to conduct the experiment.

4. Results

This part included details regarding the findings of the experiments, including descriptive analysis and structural equation modeling.

4.1. Descriptive Analysis

Table 2 reports participants' information included in the study, with males represented for 65.32% of the sampling, while females made up 34.68%. Nearly half of the participants were less than 25 years of age (49.19%), one third of the respondents (30.65%) was between the ages of 26 and 35, a proportion of the participants (15.32%) was between the ages of 36 and 45 and a small number of samples (4.84%) was over 45. In terms of education level, more over half of the participants (51.21%) had a bachelor's degree or were enrolled in university, almost half (47.58%) had a master's degree, and only a few had a Ph.D degree (1.21%). Overall, the sample size of this study met the requirements recommended by Sober [47] (177)

Table 2 Participants Profiles

Variable	Item	Frequency	Percent
Gender	Male	162	65.32
	Female	86	34.68
Age	18 – 25	122	49.19
	26 – 35	76	30.65
	36 – 45	38	15.32
	Over 45	12	4.84
Level of Education	PhD	3	1.21
	Master	118	47.58
	Undergraduate	127	51.21
Total		**248**	**100**

The descriptive statistics of mean and standard deviation of the measures were depicted in Table 3. Here, all average scores are greater than the mid-point (2.5) of the 5-point Likert scale, and standard deviations range between 0.745 and 1.193

Table 3 Mean and Standard Deviation (SD)

Construct	Item	Mean	SD
Knowledge	KD1	4.440	0.869
	KD2	3.813	0.905
	KD3	3.730	0.897
	KD4	3.723	0.980
Awareness	AW1	3.385	1.021
	AW2	3.119	1.102
	AW3	3.168	1.193
Social Influence	SI1	3.796	0.835
	SI2	3.619	0.963
	SI3	3.768	0.949
Policy	PO1	4.440	0.745
	PO2	4.239	0.752
	PO3	4.381	0.754
Facilitating Conditions	FC1	3.601	0.962
	FC2	3.731	0.853
	FC3	4.381	0.754
Digital Transformation Adoption	DTA1	3.739	0.776
	DTA2	3.792	0.765
	DTA3	3.737	0.816

4.2. Structural Equation Modeling

Each factor's internal consistency and convergent validity were reported in Table 4. In the presence research, Dillon–Goldstein's rho (RHO) was used to assess the internal consistency and reliability criteria of each construct. RHO, similar to Cronbach's alpha, helps to measure the reliability of a set of survey items, while simultaneously relaxing the assumption that each variable is equally important in defining the latent variable [41]. Instead, it is based on the model outputs (i.e., the loadings). As such, it is seen to be a better indication than Cronbach's alpha [41], [42]. The experimental results indicated that all RHOs' values are larger than 0.7, exceeding the threshold reliability recommendation [41], [43]. The Average Variance Extracted (AVE) is one approach to determine a scale's convergence value. This index is defined as the sum of the mean squares of the observable variables' normalized load coefficients in a latent variable.

Kline [41] proposed that an AVE's value of 0.5 or greater indicates that the latent variable will explain more than half of the variation of its observable variables, and that the scale has good convergence. The experiment findings revealed that the AVE scores were more than 0.5, indicating convergent validity.

Table 4 Internal consistency and convergent validity

Construct	Item	RHO	AVE
Knowledge	4	0.890	0.646
Awareness	3	0.883	0.716
Social Influence	3	0.848	0.651
Policy	3	0.881	0.711
Facilitating Conditions	3	0.856	0.665
Digital Transformation Adoption	3	0.845	0.646

Table 5 provided the experiment results from the loading estimate simulation, including the estimate, standard error, 95% bootstrap confident interval lower-bound and upper-bound. 100 bootstrap samples were used to calculate the confidence intervals (CIs). At the 0.05 level, parameter estimations were regarded statistically significant if the 95% bootstrap confident interval did not contain zero [41],[42],[43]. According to Table 5, all of the estimated loadings were statistically significant, indicating that all of the items were valid predictors of the constructs.

Table 5 Estimates of loadings.

Indicators	Estimate	Std.Error	LB	UB
KD1	0.802	0.025	0.761	0.851
KD2	0.847	0.017	0.814	0.877
KD3	0.836	0.015	0.801	0.868
KD4	0.785	0.022	0.745	0.832
AW1	0.815	0.017	0.785	0.848
AW2	0.896	0.009	0.877	0.912
AW3	0.826	0.016	0.794	0.853
SI1	0.716	0.030	0.655	0.770
SI2	0.851	0.016	0.817	0.884
SI3	0.846	0.017	0.804	0.874
PO1	0.859	0.012	0.836	0.882
PO2	0.845	0.017	0.810	0.876
PO3	0.826	0.020	0.788	0.867
FC1	0.755	0.028	0.693	0.803
FC2	0.855	0.018	0.82	0.887
FC3	0.833	0.019	0.791	0.867
DTA1	0.791	0.024	0.737	0.827
DTA2	0.829	0.015	0.797	0.856
DTA3	0.791	0.021	0.751	0.829

The experimental results provided by GSCA are shown in Table 6 including FIT, Adjusted FIT (or AFIT), standard error, 95% bootstrap confident interval lower-bound and upper-bound. The parameter estimation is considered statistically significant if there is no zero value between lower-bound and upper-bound [43]. In Table 6, FIT is the ability to explain the amount of variance by a model specification, its value ranges from zero to one. The higher fit value, the better the model can explain data. In this experimental set up, the model explains 52.5% the amount of variance in the data (Std.Error = .121, 95% CIs = .404 – .646). AFIT is similar to FIT but takes into consideration model complexity. Among competing models, the model with the highest AFIT value may be preferred, AFIT = .523 (Std.Error = .017, 95% CIs = .506 – .540). The goodness-of-fit index (or GFI) and standard root mean square residual (or SRMR) quantify the similarity between sample covariance and covariance as a further measure of total model fit. GFI levels close to 1 and SRMR values close to 0 may be regarded as excellent fit. The experimental results showed that the GFI value was nearly one (GFI =.981, Std.Error =.005, CIs =.973 -.982), while the SRMR value was nearly zero (SRMR =.039, Std.Error =.014, CIs =.348 -.407).

Table 6 Model FIT

Measures	Estimate	Std.Error	LB	UB
FIT	0.525	0.121	0.404	0.646
AFIT	0.523	0.017	0.506	0.540
GFI	0.981	0.005	0.973	0.982
SRMR	0.039	0.014	0.348	0.407

Table 7 highlighted the structural model's estimations of path coefficients from the GSCA technique, along with their standard errors and 95% bootstrap confident interval lower-bound and upper-bound. The experimental results indicated that knowledge had a positive and statistically significant impact on digital transformation adoption of participants (H1 =.136*, Std.Error =.039 , 95% CIs =.013 –.178). However, the hypothesis that awareness was a predictor of digital transformation adoption was not supported due to the presence of zero value between the confident interval lower-bound and upper-bound (H2 =.071, Std.Error =.043 , 95% CIs = -.006 - .158) but this factor had a positive effect on knowledge of digital transformation (H3 =.268* , Std.Error = .051 , 95% CIs = .156 - .364).

An analysis of social influence showed that this latent variable had a positive and statistically significant influence both digital transformation adoption (H4 = .167* , Std.Error = .055 , 95% CIs = .064 - .269) and knowledge (H5 = .136* , Std.Error =.05 , 95% CIs = .0024 -.239). Furthermore, facilitating conditions were verified as a positive predictor of digital transformation adoption (H6 = .178*, Std.Error = .049 , 95% CIs = .074 - .266). Finally, policy had a positive effect and statistically significant on both digital transformation adoption (H7 = .084* , Std.Error = .039 , 95% CIs = .013 - .178) and social influence (H8 = .109* , Std.Error = .044 , 95% CIs = .034 - .198).

Table 7 Estimates of path coefficients.

	Estimate	Std.Error	LB	UB
KD → DTA (H1)	0.136*	0.039	0.013	0.178
AW → DTA (H2)	0.071	0.043	-0.006	0.158
AW → KD (H3)	0.268*	0.051	0.156	0.364
SI → DTA (H4)	0.167*	0.055	0.064	0.269
SI → KD (H5)	0.136*	0.05	0.002	0.239
FC → DTA (H6)	0.178*	0.049	0.074	0.266
PO → DTA (H7)	0.084*	0.039	0.013	0.178
PO → SI (H8)	0.109*	0.044	0.034	0.198

* statistically significant at 0.05 level.

5. Discussion

In the following subsections, we addressed the theoretical implications with which our research aligned and to which it added to the existing body of knowledge. In addition, practical implications offered educators and policymakers insight into how to intervene to increase DT readiness. As a consequence, interested researchers should interpret the data with caution due to the limitations of the present study.

5.1. Theoretical Implications

Perhaps, the amount of variance explained by the conceptual model specification is one of the most notable findings in this study. That is, the model explains 52.5% the amount of variance in the data. Furthermore, the experimental results verified the majority of the proposed hypotheses. The only exception was that the awareness factor was not found to have an impact on the digital transformation adoption.

This is an astonishing result, which departed from the findings of several studies in the literature [48],[49], [50], in which context-awareness was considered as a reliable predictor on behavioral intention. The reason for this inconsistent finding may be attributed to the roles of television and news in recent years [51]. With the advancement of smartphones and tablets, people are moving from watching TV, reading traditional newspapers to entertaining subscribed channels on the internet with their on-the-move devices. In this regard, important information may not reach out handheld users, including digital transformation updates. Evidence from Table 2 also showed that standard deviations for this kind of question are high, indicating a fluctuation in the responses. Regarding the positive influence of knowledge over digital transformation adoption (H1 = .136, Std.Error = .039, 95% CIs = .013 – .178), this study affirmed the findings of previous studies in understanding behavioral intention adoption [33], [34]. Indeed, knowledge is required in order to embrace digital transformation; otherwise, the possible future digital transformation adopters would be unable to transform tasks and operational procedures that they do not realize [48]. The effect of knowledge on behavioral intention can be explained through relying on the theory of planned behavior where the authors proposed that knowledge may also be utilized to anticipate a person's willingness to perform a particular behavior. Examining the AW → KD path indicated that awareness positively influenced on knowledge of digital transformation (H3 = .268, Std.Error = .051, 95% CIs = .156 - .364). The current result reinforced the findings [52], [53], [54] where the authors found out a significant relationship between awareness and knowledge. Yet, in order to get an understanding of a subject, its presence or awareness must be exhibited. As a consequence, researchers and interested readers can use this experimental finding to supplement their research assumptions in a subsequent study. In terms of exploring the relationship between social influence and digital transformation adoption, the statistical result of SI over DTA (H4 = .167, Std.Error = .055 , 95% CIs = .064 - .269) indicated that teachers, students and government personnel were influenced by their colleagues and friends in order to adopt digital transformation. Adopting digital transformation necessitates the participation of all stakeholders to ensure that the system and process are consistent. According to Nguyen [37] , social influence is a predictor of behavioral intention as it leads to increasing the perceptions of users toward employing a new technology.

The assertion on the role of social influence in predicting users' behavioral intention to adopt a new technological system has been investigated in a number of studies [28], [55]. Regarding the impact of social influence over knowledge, the experimental result provided a positive and statistically significant effect (H5 = .136, Std.Error = .05 , 95% CIs = .0024 - .239). The current study finding verified this interaction investigated in the literature [56] where the authors found a significant relationship between social influence and knowledge. This phenomenon might be explained exclusively by the social cognitive theory [57], which holds that individuals' attitudes and knowledge are influenced by the society in which they live. The statistically significant evidence regarding the influence of facilitating conditions on digital transformation adoption (H6 = .178, Std.Error = .049, 95% CIs = .074 - .266) reflects the extent to which increasing the availability of supporting devices would improve the likelihood of embracing digital transformation. The current study validated the findings of previous studies in understanding behavioral intention adoption [28], [37]. That is to say, adopting digital transformation necessitates while using a certain technological device, such as a computer, tablet, or smartphone in empowering efficient and successful transformation. Furthermore, regarding the positive effect and statistically significant of policy over digital transformation adoption (H7 = .084, Std.Error = .039 , 95% CIs = .013 - .178), this study affirmed prior research findings [58] that when individuals viewed technology-related policy as essential and clear, they were more motivated to employ technology. Finally, investigating the PO → SI path indicated that policy positively affected on social influence (H8 = .109, Std.Error = .044 , 95% CIs = .034 - .198). In this case, policy had both direct and indirect effects on the likelihood in adopting digital transformation. As such, it is regarded as an important factor that should be investigated in a similar context.

5.2. Practical Implications

"Transform or perish" or "digitalize or perish" is probably the most mentioned slogan in the world and in Vietnam in the past 2 years [59]. Many practical lessons have demonstrated that successful digital transformation necessitates the involvement of all stakeholders. The Vietnamese government, acutely aware of the importance of digital transformation in the economy and society, has conducted several initiatives and training programs to raise awareness about the role of digital transformation for citizens.

Despite the fact that this effort was carried out through a number of channels (e.g., news, government websites, documents, television, social networks), the findings from this study did not demonstrate a favorable effect in terms of awareness. That is, the adoption of digital transformation cannot be predicted by the awareness factor. In other words, exposing more information on digital transformation would not increase the possibility that employees who participated in the training program will embrace digital transformation for their job in the future. As a result, decision-makers should reconsider these strategies in a more cautious manner. The experimental results supported the remaining assumptions in the proposed conceptual model, which states that facilitating conditions, policy, social influence, and knowledge are reliable predictors of digital transformation adoption. As such, the following recommendations were made. First, a clear policy should be established at all institutional and organizational levels, and that policy should encourage rather than force individuals to actively participate in this transformation effort. Second, in terms of knowledge, the role of higher education should be emphasized as it supports digital literacy strategies for all citizens. At this time, teachers/instructors become the guides rather than promoting a single pedagogical approach. Furthermore, learning and training program should be research-based approach as it was considered one of the plausible approaches for digital transitions [60]. Third, encouraging individuals to explore new technologies; only after they have experience with new technology and realize the benefits recommend it to friends and colleagues. And finally, decision makers should consider hiring or subscribing instead of purchasing or owning since it can greatly cut total costs in the beginning, thereby enhancing facilitating conditions.

5.3. Limitations

Although the study yielded a credible conclusion by validating the plurality of the assumptions, it was unavoidably constrained by a number of limitations. When taken along with the unanticipated findings, these limitations point to a promising setting for further research. First, this study employed purposive sampling technique to recruit participants from the massive training programs (over 2,500 prospective adopters per province in 2025). Despite widespread acceptance in the literature, this sampling method restricts the generalization of the results. The second limitation is the sample size when compared to the target population at the large scale.

However, using too many samples in the research would reduce the statistical power, or the ability to make inferences. Therefore, as noted in the method section, the investigators maintained a proportion of samples suggested by the literature. And finally, many other factors that may impact digital transformation adoptions, as described in earlier theoretical models, were not included in this study. This is because, throughout the early stages of transition, educators and decision makers regarded the factors covered in this study as the most significant.

6. Conclusion

This study investigated the factors that influence individuals` perceptions to adopt digital transformation. Based on the analysis of 248 participants from various sectors, the experimental results validated the majority of the expected assumptions among factors in the proposed conceptual model. Hence, facilitating conditions, policy, social influence, and knowledge had a positive and significant influence on digital transformation adoption. The significant exception was that awareness factor which didn't have an impact on the digital transformation adoption. Overall, the model explains 52.5% the amount of variance in the data. The impact of the current research was justified through theoretical and practical implications. Four recommendations were proposed for practitioners, and limitations were roughly discussed. Future study is needed to re-examine the unexpected effect of awareness on digital transformation adoption.

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