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The Technology Readiness of Thai Governmental Agency*

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Abstract

The paper aims to analyze the factors influencing the digital technology readiness of the governmental agency in Thailand, namely the Office of the Welfare Promotion Commission for Teachers and Educational Personnel (OTEP). This paper discusses challenges regarding the technology readiness of OTEP, which is taken as a case study for Thai governmental agencies. Data is collected through questionnaires distributed from October to December 2020. With a population of 777 OTEP staff, 534 employees are the respondents of this study. The study employs correlation, multiple linear regression, and structural equation modeling to analyze the data. The dependent variable is the digital technology readiness, while the independent variables are age, technology literacy, technology experience, attitude, organizational culture, leadership, and learning facilities. One of the principal findings is that the digital technology readiness of OTEP is at a moderate level. In addition, learning facilities, technology literacy, leadership, and organizational culture are found to be statistically significant for digital technology readiness. The findings highlight the issues and obstacles associated with encouraging human resource development, notably in the field of digital technology. Adopting digital technology to give better services to a large scale of customers is challenging for most large governmental enterprises, considering OTEP as a wonderful example for organizations under government oversight.

Keywords: OTEP, Digital Technology Readiness, Technology Literacy, Attitude, Culture

JEL Classification Code: M15, M48, O14, O30

1. Introduction

Digital technology has developed rapidly. Both government and private organizations have been working to implement digital technology to increase the efficiency of their operations and respond to the ever-changing expectations of their customers and citizens. Digital transformation plays an essential role in changing bureaucratic and organizational culture and stakeholder relationships (Mergel et al., 2019). The ability to adapt to digitalized technology is crucial for the development and growth of businesses and organizations.

In 2016, the government of Thailand announced the 4.0 policy for "stability, wealth, sustainability" (Kohpaiboon, 2020; Ministry of Industry, 2016; National Productivity Institute, 2018). The 4.0 policy drives national reform in various fields to improve, correct, organize, adjust direction, and create a path for national development and thus cope with the rapidly changing opportunities of the 21st century. Furthermore, the adoption of digital technology is believed to be one of the factors that will drive Thailand toward prosperity and sustainability.

In the literature, the terms "technology readiness" and "digital readiness" are used interchangeably. However, it has a variety of connotations. The readiness of individuals, organizations, and segments of the economy to introduce and utilize novel digital technologies to enhance the advantages of these innovations is the primary definition (Alzhanova et al., 2020).

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The Office of the Welfare Promotion Commission for Teachers and Educational Personnel (OTEP) was established under the Teachers and Education Personnel Council Act 2003 under section 67. OTEP is a juristic person under the supervision of the Ministry of Education and has roles, duties, and responsibilities for promoting the welfare and other benefits to stabilize and improve the quality of life of educational professionals and practitioners. OTEP is used as a case study in this study.

OTEP's main office is located in Bangkok, Thailand, with sub-branches in all 77 provinces of the country and 777 staff members. The mission of OTEP is to assist teachers and educational personnel regarding matters such as loans, training costs, assistance for the elderly, and funeral allowances. These services are intended to assist members from the first year of their careers until their death or withdrawal of their membership. The service period for one person can be as long as 60 years or more. Currently, OTEP has over one million members throughout the country. To provide efficient services to its members, using digital technology both at management levels and providing services is essential. However, as a civil agency, it is not easy to change from a bureaucratic system to a somewhat new, adaptive, and technologically efficient agency. Even though digital transformation is encouraged across the country under the government policy—Industry 4.0—transforming any organization is a long process and needs significant support in terms of budget and changing people's mindset. In this digital era, where technology disruption comes to all, how ready is OTEP to adapt its operations to these changes? This is the question that underpins this research.

2. Literature Review and Hypotheses

Several theories describe the foundations of human behavior and are used as a framework for studying the factors that influence individual attitudes, such as the willingness to accept modern technology, accept mobile operating systems, and obtain information systems in organizations. Theories concerning individual intention are rooted in human psychology. The theory of reasoned action (TRA), developed by Ajzen and Fishbein (1980), explains the relationship between attitudes and behavior in human action and can be used to predict how a person will behave based on pre-existing attitudes and behavioral intentions. This theory considers the factors relevant to or influencing human decision-making, which in turn affect individual behavior.

The theory of planned behavior (TPB) is another important theory that looks at the cognitive elements that influence self-regulation or self-behavior. This social psychology hypothesis was created by Ajzen (1985, 2011), who claims that persons believe they have control when they have the means and chances to carry out specified activities. To put it another way, when workers believe they have the resources they need, they are more willing to take on new challenges.

The technology acceptance model (TAM) is an information systems theory that models how users accept and use new technology. Davis et al. (1989) developed TAM as an extension of the TRA. TAM focuses on the elements that influence whether or not a new technology or innovation is accepted. "Perceived ease of use" (PEOU) and "perceived level of usefulness" (PLU) are two characteristics that directly influence a user's acceptance of technology or innovation (PU). Furthermore, these models suggest that a person's age has a substantial impact on whether or not they accept or reject technology.

The techniques of TRA, TPB, and TAM have been widely used to better understand the behaviors of people who adopt new technology. Private businesses and governments all across the world are adopting and expanding the use of advanced technologies. Government agencies are responsible for providing information and services to citizens (G2C), businesses (G2B), and governments (G2G) (G2G) Electronic government, often known as e-government, is a phenomenon that all governments are experiencing and is a fundamental component of their transition. It serves a variety of purposes, including openness, accountability, and good governance. The government becomes more results-oriented, efficient, and citizen-centric as a result of this transition.

Several factors were studied in-depth to identify the critical success factors for technology adoption and its readiness, including the age, knowledge, experience, and attitudes of the users, which might positively or negatively influence technology readiness. Alzhanova et al. (2020) proposed a methodology for assessing the level of the digital readiness of science using the digital readiness index of the research institute, calculated based on four criteria: equipment availability, software, personnel, and digital skills, consumers, for instance. In addition, organizational factors such as the organization's culture, the leadership and management of the organization, and the learning facility provided by the organization are critical factors for the technology readiness of an organization. Underpinned by the theories mentioned above and previous research literature review, the hypotheses are set as follows.

The characteristics of digital technology users, such as age, may have an inverse influence on digital technology readiness. Yang and Shih (2020) used TAM and UTAUT to explore the influence of cognitive age on technology acceptance behavior by two different groups: digital natives (those who are younger than 34) and not digital natives (older than 34 years old). They found that younger people—digital natives and digital immigrants (those who perceive themselves to be younger than their chronological age)—held better PU, PEOU, and flow significantly.

In addition, research also defines the generations in which people belong, either Baby Boomer (1945−1964), X (1965−1981), *Y* (1982−1994), or *Z* (1995−2010). However, these generational cutoff points are not an exact science and should be viewed primarily as tools allowing for purposive analyses. However, their boundaries are not arbitrary, and even though there are no agreed-upon years in which each generation should begin, the characteristics of each generation are generally agreed upon. Generation differences are more likely to impact the attitudes and core values of employees in the organizations and affect individual performance when it comes to technology assignments (Widagdo & Susanto, 2016). These findings underpin the first alternative hypothesis of this present study: the younger the users, the better they adopt new technology.

H1: *Age is negatively correlated with digital technology readiness.*

The ability to use technology to identify, analyze, develop, and communicate knowledge is known as digital literacy. People can benefit from an understanding of a wide variety of technologies in addition to a working knowledge of computer software and hardware (e.g., word processing, presentations, and web-based resources).

Other factors affecting the readiness for adopting digital technology are a lack of time and limited technical knowledge and skills. In addition, equipment availability and technical support are essential. The Thai government's "Industry 4.0" requires the workforce and management to have digital literacy, technology literacy, and, of course, human literacy. Therefore, knowledge and experience in using technology are fundamental to acquiring necessary skills.

Digital technology literacy includes the ability to use computer office programs (Word, Excel, and PowerPoint), email, social media, digital media, digital storage, online form creation, and big data. Government agencies are beginning to utilize big data technology to analyze large data sets in science and research, as well as mine data, to prevent terrorist attacks and/or waste, fraud, and abuse (Lee, 2020a). The government's ambition is to ensure that the information will be analyzed correctly and come to the right persons and right time. Technology literacy and experience are, therefore, the critical elements to this. Experience in digital technology includes, but is not limited to, experience in using computer office programs, social media, purchasing or selling products/services using an online platform, using communication applications, storing information on a cloud system, and experience in analyzing big data. The levels of literacy typically start from a fundamental level to an intermediate and advanced level. Thus, both digital literacy and experience go hand-in-hand (Alba & Hutchinson, 1987). This leads to the following two hypotheses.

H2: *Technology literacy is positively correlated with digital technology readiness.*

H3: *Technology experience is positively related to digital technology readiness.*

According to Ajzen and Fishbein (1980), attitude and subjective norms are critical variables in developing behavioral intentions, a claim supported by TAM. Users who have a favorable attitude toward technology are more likely to be happy with the system and consider it more useful (Ajzen & Fishbein, 1980). As a result, it is predicted that user attitude has a favorable impact on PU and behavioral intention.

H4: *Attitude is positively correlated with digital technology readiness.*

Corporate culture and technology adoption are two of the most critical issues facing large-scale organizations. Organizations operate in an increasingly uncertain, networked, and decentralized environment in which the adoption and use of information technology have become central to fulfilling their missions. To examine the influence of corporate culture on an individual's willingness to accept technology, Melitski et al. (2010) reviewed the theory of behavioral intent, technology adoption, and organizational culture and proposed a model for examining technology acceptance in public organizations. People's attitudes and perceptions affect their behavior, such as their readiness to use mobile phone applications, social media, or online financial transactions. These understandings lead to the following hypothesis.

H5: *Organizational culture is positively correlated with digital technology readiness.*

Most organizations today ensure that their senior executives are highly competent, particularly C-Level executives such as chief information officers (CIOs) and chief technology officers (CTOs), who are organizations' leaders in the area of formulating business strategies. Their recommendations lead to a competitive advantage by creating and adding sustainable value to their organization.

Organizations are not just successful because of the technology they adopt but rather because of the quality of leadership, communication and planning, and managers' interpersonal skills. An organization with good leaders is the key to success. Guo et al. (2015) believed that strong leaders are critical in helping their organization have technology readiness through making the necessary changes in the organization's culture. E-leadership is found to influence the employee's performance (Wolor et al., 2020). Leaders who are literate in digital technology can expand an organization's intelligence and data warehousing and facilitate a more effective workflow. That digital technology readiness is the job of an organization's leadership leads to the following hypothesis.

H6: *Leadership is positively correlated with digital technology readiness.*

Organizational readiness requires accessible educational resources. It is also dependent on several operator factors; for example, the teachers in educational institutions must have the necessary knowledge and technological skills. Furthermore, the availability of the required tools and technologies is a fundamental factor in adopting digital technology. Shonhe (2019), who researched librarians in Bostwana, found that librarians are equipped to provide information and communication technology but only to their basic library services. Thus, technological services remain limited.

The problems faced by the sample of librarians include low bandwidth Internet connections and a lack of basic computer equipment, while the technological skills of the librarians themselves also remain at a low level (Shonhe, 2019). Thus, professional development opportunities are also crucial if librarians are ready for technological advancement in librarianship. In online classes, the roles of facilitators and learner performance are intertwined, influencing each other. Both quality and quantity of learning facilities relate to learner performance, which is greatly influenced by the facilitators (Lee, 2020b).

To help people gain the skills, learning facilities such as e-training or e-learning tools/facilities could be set up. E-training is comparable to e-learning in many ways, most notably in the delivery method and technology used. It does, however, refer to a considerably shorter learning period that is usually focused on achieving a certain learning goal or skill.

In this situation, resources also refer to the materials that organizations make available and accessible to users, such as materials provided by organizations, training offered or sponsored by organizations, or processes that assist users in becoming digitally ready. The greater the level of digital technology readiness, the more help supplied by organizations.

H7: *Learning support services are positively correlated with digital technology readiness.*

The factors that have a potential influence on digital technology readiness are illustrated in the research framework below (See Figure 1).

3. Methodology

3.1. Study Population and Number of Respondents

OTEP. Some 534 people responded to our questionnaire—about 70% of the response rate. The questionnaire was delivered from October to December 2020. Of those who participated, 76.59% were females, and 23.41% were males. The age of respondents ranged from 21 to 69 years of age, with an average age of 42 years. Regarding the number of

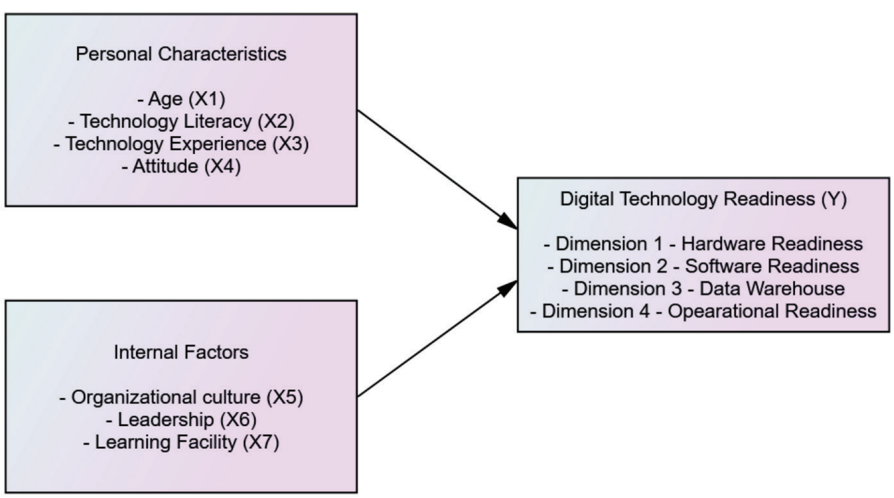

Figure 1: Research Framework

working years, the range was from less than one year to a maximum of 46 years, with an average of 11 years of work. The majority of the respondents were junior executives (79.96%), who hold bachelor's degrees (64.23%) in business administration, management, marketing, and accounting (45.13%). In addition, the majority of the respondents worked in the provincial offices of OTEP (57.30%).

3.2. Research Methods

A questionnaire consisting of 57 items was used to collect data. A Likert scale (1−5) was employed, in which one (1) is "the least used," "never used," or "most disagree" and five (5) is "the most used," "regularly used," or "most agree". Thirty respondents participated in a pre-check of the questionnaire's reliability. Cronbach's alpha was used to determine internal reliability; items show reliability when scored 0.70 or above. See Table 1.

This study employs multiple linear regression (MLR) to model and explain the relationship between numerous explanatory (independent) and response (dependent) variables. Empirically-based computational social influence models, according to Flache et al. (2017), can contribute to a good and solid understanding of crucial societal challenges. We discovered a requirement for substantial empirical data beyond typical MLR in the case of OTEP. In this study, we used structural equation modeling (SEM) in addition to multiple regression models to assess the internal consistency of the findings.

3.3. Model Identification

Model detection, which occurs when latent variables are estimated, is frequently overlooked. Kline (2015) proposed three factors for selecting the appropriate SEM model: (1) every latent variable (including residual terms) must be assigned a scale, which means that either the residual terms' path coefficient or one of the latent variable's loading factor must be fixed to 1, or the variance of a latent variable must be fixed; (2) every latent variable (including the residual terms) must be allocated a scale, which means that one of the residual terms' (disturbance) path coefficients and one of the latent variable's loading factors must be assigned a scale; (3) the degrees of freedom (df) value must be included, which is typically presented with a figure greater than zero. All confirmatory factor analysis models have at least two indicators for each latent variable, which is a prerequisite. On the other hand, many studies fail to scale the latent variables before the estimate, resulting in erroneous results. In detail, a causal test cannot rely on an unscaled latent variable as the model may fit by chance.

3.3.1. Estimation Methods

The estimating methods utilized in SEM are maximum likelihood (ML), generalized least squares, weighted least squares, and partial least squares. The default estimate approach in many SEM software products is ML estimation (Hoyle, 2011; Kline, 2015). The estimate methods were

Table 1: Variables used in the Present Study

Variables	Variable Name	Description	Cronbach's Alpha
Y	Digital technology readiness	The level of digital technology in the organization is divided into four dimensions	
	Dimension 1: Hardware	Readiness of hardware: both in quality and quantity	0.917
	Dimension 2: Software	Readiness of software, both in quality and quantity	0.852
	Dimension 3: Data warehouse	Readiness in data warehousing in the organization	0.937
	Dimension 4: Operations	Operational readiness in the use of digital technologies	0.938
X1	Age	Employees' age	n.a.
X2	Technology literacy	Employees' knowledge in the use of basic operational systems	0.927
X3	Technology experience	Experience in using technology-related tools and software	0.900
X4	Attitude	Expressions of likes and/or dislikes toward using digital technology	0.916
X5	Organizational culture	Behaviors relevant to modernization and adaptation	0.800
X6	Leadership	The ability of leaders to lead personnel in the organization	0.918
X7	Learning facilities	Learning resources to enhance learning in digital technology	0.921

n.a. – not available.

all claimed to be ML-based, which requires that (1) the variables' joint distribution has no skewness or kurtosis (e.g., multivariate normality); (2) the variables are continuous; and (3) there is minimal missing data, i.e., less than 5% (Hoyle, 2011; Kline, 2015). The variables in this study satisfy these requirements.

3.3.2. Report of Model Fit Indices

Reporting fit indices are highly recommended and required in any SEM. Model fit indices are given in 93.8% of publications. None, however, explain why they used the fit indices they chose. Those who do not report model fit indices also do not explain why they did not. χ^2, comparative fit index (CFI), root mean square error of approximation (RMSEA), Tucker–Lewis index (TLI), the goodness of fit (GFI), normed fit index (NFI), standardized) root mean square residual (SRMR), Akaike's Information Criterion (AIC), and Bayesian Information Criteria (BIC)ˀ are commonly used in these publications. Almost every paper includes χ^2 because it is the most reliable indicator of model fitness. Despite the lack of substantial χ^2 studies, some publications published their SEM findings, and GFI and NFI are also used.

Model fit indices are good indications of how well a model works. However, numerous aspects, such as data distribution, missing data, model size, and sample size, influence their diverse qualities. (Hu & Bentler, 1999). In addition, most fit indices (e.g., χ^2, CFI, RMSEA, TLI, GFI, NFI, SRMR) are affected by multivariate normality (i.e., a property of the ML method that is applied in SEM). On the other hand, CFI, RMSEA, and SRMR help detect model misspecification, whereas relative fit indices (e.g., AIC and BIC) are largely employed for model selection.

3.4. Variables Used in This Study

The variables used in this study consist of the dependent variable (Y), digital technology readiness. There are seven independent variables (X1–X7); the first four are individual characteristics, whereas the last three are internal organizational factors. Table 1 describes the meaning and number of items for each of the variables.

4. Results

Table 2 shows the correlation coefficients between variables X1–X7. The association between the two variables is shown in each cell of the table. The data reveal, for example, a strong correlation between technology literacy (X2) and technology experience (X3) with a coefficient of 0.77 (p-value < 0.01).

None of the variables has a variance inflation factor (VIF) greater than 3.0. A VIF below 1.0 is considered acceptable (Hair et al., 2010). Thus, statistically, all the variables reveal no multicollinearity issues and can be used as variables in a multiple regression equation.

As noted later, this correlation matrix can be used as a summary of the findings and inputs for more advanced analysis or as a diagnostic tool.

Table 3 shows that the respondents had a moderate technology readiness level (Y means equal to 3.05 out of 5.00, with a standard deviation of 0.82). Among the four dimensions, dimension 1 (Hardware readiness) had the highest mean score, at 3.22. The respondents have a good attitude (X4) toward technology with a mean score of 3.83, while the lowest mean score is technology experience (X3), with a mean of 2.64. The mean score of each variable is presented in Table 3.

All independent variables passed the multiple regression assumptions. Thus there appear to be no issues of collinearity and multicollinearity. As a result, the variables can be used in a regression to look into the factors that influence OTEP's digital technology readiness. Table 3 displays the findings of the MLR analysis using a stepwise selection strategy. The independent variables learning facilities and opportunities (X7), organization culture (X5), technology literacy (X2), and

Table 2: Correlations

Variables		X1	X2	X3	X4	X5	X6	X7
Age	X1	1						
Technology literacy	X2	0.01	1					
Technology experience	X3	–0.02	0.77**	1				
Attitude	X4	–0.06	0.53**	0.54**	1			
Organizational culture	X5	0.00	0.31**	0.31**	0.49**	1		
Leadership	X6	–0.05	0.20**	0.21**	0.31**	0.71**	1	
Learning facilities	X7	–0.01	0.25**	0.29**	0.20**	0.54**	0.63**	1

n = 53.4 **Correlation is significant at the 0.01 level (2-tailed).

Table 3: Mean and Standard Deviation of Variables

Variables*	Label	Mean	Standard Deviation
Technology readiness	Y	3.05	0.82
Hardware readiness	Dimension 1	3.22	1.10
Software readiness	Dimension 2	3.18	1.02
Data warehouse	Dimension 3	2.86	1.09
Operational readiness	Dimension 4	2.96	0.93
Age	X1	41.50	9.64
Technology literacy	X2	2.84	0.82
Technology experience	X3	2.64	0.84
Attitude	X4	3.83	0.89
Organizational culture	X5	3.63	0.80
Leadership	X6	3.47	0.92
Learning facilities	X7	2.89	1.02

*Rating scale of 1–5 is applied to each item in the questionnaire, except age.

Table 4: Summary of Coefficients of Variable Related to Digital Technology Readiness

Model[a]	Non-Standardized Coefficients		Standardized Coefficients	*t*	*p*-value	Test Result
	B	Std. Error	Beta			
Constant	0.24	0.11		2.08	0.04*	
Learning facilities (X7)	0.37	0.03	0.45	12.91	0.00**	Hypothesis 7 is supported
Organizational culture (X5)	0.15	0.04	0.15	3.69	0.00**	Hypothesis 5 is supported
Technology literacy (X2)	0.21	0.03	0.21	7.44	0.00**	Hypothesis 2 is supported
Leadership (X6)	0.18	0.04	0.20	4.69	0.00**	Hypothesis 6 is supported

[a]Dependent Variable: Digital Technology Readiness; ***p*-value < 0.001 Significant at the 0.01 level, **p*-value < 0.05 Significant at the 0.05 level.

leadership (X6) were all statistically significant predictors of technological readiness at a rate of 62.10, the highest of the four. The findings show that learning opportunities and facilities (X7) had the highest standardized coefficient at 0.45 (Beta = 0.45, $p < 0.01$), followed by technology literacy (X2) at 0.21 (Beta = 0.21, $p < 0.01$), leadership (X6) at 0.20 (Beta = 0.20, $p < 0.01$), and organizational culture (X5) at 0.15 (Beta = .15, $p < 0.01$). When the learning facilities, technology literacy, leadership, and organizational culture increase by 1 unit, technology readiness increase by 0.45, 0.21, 0.20, and 0.15 standardized units, respectively (see Table 4). With all things being equal, the standardized equation of MLR analysis of this analysis is presented:

$$Y = 0.45(X7) + 0.21(X2) + 0.20(X6) + 0.15(X5) \tag{1}$$

It is important to note that if the company has the necessary budget and capital to spend on new infrastructure, the first three aspects can be enhanced quickly. However, the final pillar, operational readiness, necessitates more time and resources, both in terms of infrastructure and human resource development, and so is not a "fast cure." See Table 4.

To assure the influence of the response variables, we performed an SEM to find the cause and effect of the variables. The following model integrates and correlates all factors and provides a structural link from the independent variables process to the dependent variables, as shown in Figure 2. In Figure 2, some variables are not presented due to no correlation. For example, age (X1) and technology experience (X3) are not related to the response variables, while operational readiness (dimension 4) is not presented

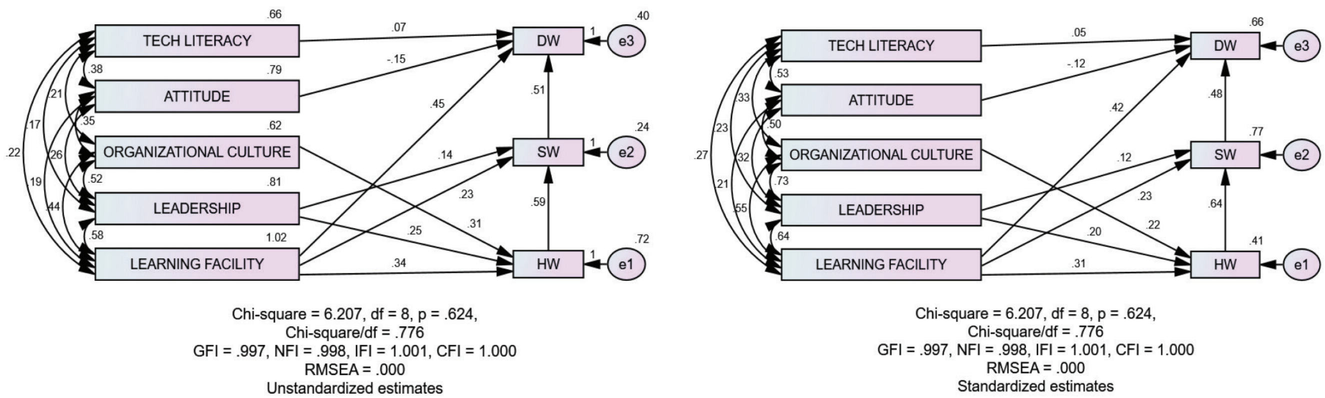

Figure 2: Unstandardized and Standardized Estimates of SEM
Created by the Author's Work

for the same reason. Straight lines from explanatory variables pointed to response variables are presented with figures of ß (Figure 2—on the left: Unstandardized) and beta (Figure 2—on the right: Standardized). Where the lines are not presented, means no correlations between variables.

Figure 2 shows the achieved stable model fit estimation by which the indicators of fit: cmin/df = 0.776 (Cmin = 6.207, df = 8); GFI = 0.997; NFI = 0.998; IFI = 1.001 and CFI = 1.000; RMSEA = 0.000. In sum, Figure 2 shows that learning facility has a highly significant influence (unstandardized regression weight = 0.45, p = 0.0001) on data warehouse (DW), while for influence software (SW) and hardware (HW) at coefficient 0.23 and 0.34 KM, respectively, both p-values equal 0.0001. Attitude has a negative impact on DW. This conclusion is significant for the organization because the samples did not have a positive opinion or, in other words, did not see their organization's DW improving despite the influence of other factors. The learning facility (X7) is the most influential factor in HW, SW, and DW modifications, as it is through this factor that leadership makes the most critical decision regarding the organization's learning facility improvement (see the double arrow where the covariance of 0.58 is the correlation between leadership [X6] and learning facility [X7]). The figure below shows that the structural model fits the data well and produces a confirming value for the good model fit. Understanding the importance of these linkages in companies is critical for organizations to improve.

With all things being equal, the standardized estimates of the structural equation model are presented on the right of Figure 2. The factor that most influences the dependent variables is the learning facility. To improve the HW, SW, and DW, the organization needs to provide full support. The readiness of these three variables, therefore, allows the staff to have operational readiness. In addition, organizational culture and leadership are highly correlated (standardized regression weight 0.73, p-value equals 0.000), while leadership and learning facility are also strongly correlated (standardized regression weight 0.64, p-value equals 0.000).

5. Discussion

OTEP currently (in 2021) has a moderate to low level of technology readiness. The highest level of technology readiness was the hardware (HW) readiness dimension. Although it was the highest dimension, it was nonetheless only at a moderate level. The multiple regression model indicates that the four influencing factors associated with digital technology readiness are learning facility (X7), technology literacy (X2), leadership (X6), and organizational culture (X5). This present study found that technology literacy (X2), attitude (X4), technology experience (X3), and learning facility (X7) are the key factors. All factors have a positive influence on operational readiness. When the two models are compared, the data revealed two similar key factors: technology literacy (X2) and learning opportunities and facilities (X7), which appear vital for OTEP to reach a high level of digital technology readiness.

Interestingly, age (X1) was not a key factor. Thus, this finding does not support the H1 hypothesis as age is not found to influence digital technology readiness. Nonetheless, the majority of the study's participants are of a specific age—the average age is 42, and the majority are from Generation X (ages 39 to 55). The majority of the respondents, 95.70 percent, belong to the babyboomer generation (7.87 percent), generation X (45.51 percent), and generation Y (42.32 percent), all of whom are technologically illiterate. In this sense, the findings contradict previous research

(Widagdo et al., 2016). However, we contend that this is due to the fact that the majority of the study's respondents are not of varying ages. As a result, the age diversity of the study's samples has a significant impact on the conclusions. Most of the respondents were older, with moderate to low technology readiness levels, which may be related to the recruitment system that still has officers whose qualifications do not match the positions.

Moreover, the results show that four main factors, namely learning facility, technology literacy, leadership, and organizational culture, significantly impact digital technology readiness when all four dimensions are taken into the dependent variable. The findings support Hypotheses 2, 5−7. While technology experience (X3) and attitude (X4) variables are not found to influence digital technology readiness. Hypotheses 3 and 4 are not supported.

In addition, the SEM confirms the findings from the MLR model. The procedure in SEM revealed that these explanatory variables have a significant influence with a higher cutoff goodness-of-fit index (GFI) >0.95 and RMSEA (spec. < 0.08). The results show that the explanatory variables—learning facility, culture (supported by Melitski et al., 2010), technological literacy (Alba & Hutchinson, 1987), and leadership (Guo et al., 2015; Wolor et al., 2020) —have strong relationships with technology readiness, as measured by hardware (HW), software (SW), and data warehouse (DW). The key findings from SEM complement the findings from the MLR model but expand the depth of the correlations between variables, where learning facility (X7) is a crucial factor influencing the hardware, software, especially data warehouse readiness and leadership (X6) influence the hardware and software readiness. Besides, culture (X5), attitude (X4), and technology literacy (X2) partly influence technology readiness. Noted that, in MLR, attitude (X4) does not influence digital literacy but is found negative influence when using SEM.

6. Conclusion and Recommendations for Future Research

The findings from this research have brought attention to how the digital technology readiness of OTEP can be enhanced. The use of big data in policymaking has become ubiquitous. Governments have invested considerably in their ability to make judgments based on substantial data inputs, regardless of their political viewpoint (Lee, 2020a, 2020b). As one of the most important government institutions, OTEP cannot avoid this responsibility. The learning facility had the greatest impact on OTEP's degree of digital technology preparedness. Although there is sufficient technology and the necessary software, a data warehouse is not a unique concept. The finding is similar to other organizations, as mentioned in Alzhanova et al. (2020). However, supporting one main factor may not fully enhance the level of readiness. Incorporating the other factors would enhance the digital technology readiness of OTEP to a higher degree. Since the learning facility is the critical item, adding more learning facilities, supporting staff for continuous learning, and providing a good platform for education are a must. We also believe that providing staff with digital technology training will help them improve their literacy and experience with the technology. Training can be customized to the level of knowledge and functional requirements of the participants. Based on the learners' level of technology literacy, training should be separated into three levels: I Basic level: office software training; ii) Intermediate level: fundamental digital and information technology training, including online communication; iii) Advanced level: specialized training based on organizational needs, such as website maintenance, access, big data analysis, statistical analysis, and dashboard visualization.

Furthermore, by offering a platform on the office's website and allocating time for self-learning, OTEP should encourage long-term learning, such as short online training courses. In the annual performance evaluation, OTEP should support constant self-learning and establish KPIs for training. Hardware and software readiness is critical to the organization's other functions. Simultaneously, a backup system, which includes a data warehouse system and a firewall system, is required to store all of the data and ensure data stability. All of them, if implemented, will assist OTEP to improve its digital technology readiness and maintaining operational resilience in the digital epoch.

This research has several limitations which future research can address. Because this study is a case study of OTEP, the Thai government's educational support unit, the conclusions can be applied to other organizations with similar features. Senior staff can be found in a number of Thai government agencies. The Thai governmental system (or bureaucracy) now has a V-shaped population pyramid, with senior civil officials outnumbering younger public servants. According to the National Statistical Office of Thailand, most government officials in the bureaucracy will be approaching retirement age in 2020, which is 55–60 years old. Thus, the bureaucratic system is full of older people (National Statistical Office, 2021). In this study, nearly 90 % of the respondents are in the generations Baby Boomer (7.87%), X (45.51%), and Y (42.32%). Generally speaking, people of these generations are not technologically competent, and changing their attitude regarding technology is not easy. This could be the main reason why the age variable (X1) was not correlated to the digital technology readiness of OTEP in this study. In addition, this might be the critical factor contributing to digital technology readiness and relevant to attitude. In the SEM, where attitude (X4) presents a negative relationship to a DW, this result suggests that the respondents of this certain age did not have positive attitudes toward advanced technology.

Research and investigation of governmental service entity models are relatively low in number. Generalizing findings from this research may be a sound basis for developing governmental organizations and future research. A generalization of this study's findings, to some extent, can be applied to other organizations, either in Thailand or outside Thailand. This is a challenging issue for case study research; however, we argue that most governmental organizations have similar characteristics. Of course, variations could range from small to large depending on several factors. Nevertheless, the environmental context of OTEP is typical of governmental organizations. The findings of this study were used to develop matrices that can be used to evaluate the technological readiness of other firms. Digital transformation has the potential to alter bureaucracy and organizational culture, as well as interactions with other stakeholders. Learning from these findings could help other firms increase demand for high-skilled technology workers and boost technology adoption. Increased investment in learning facilities and educational channels will promote technology literacy.

The rise of technology adoption and digitalization are transforming organizations, and governmental agencies are no exception. As suggested, training and learning facilities can help equip staff to be ready for the challenges of emerging technology. Future research may find the same potential factors and add more factors or variables to their studies to confirm this finding. Internal factors such as an increased budget to support digital technology, the number of years in the secretary's position, and the staff's perspective of digital technology can all be regarded as new variables. External variables including GDP, government budget growth to support digital technology, and Thai residents' digital literacy are all suggested new variables for future research.

References

Ajzen, I. (1985). From intentions to actions: A theory of planned behavior. In J. Kuhl & J. Beckman (Eds.), *Action-control: From cognition to behavior* (pp. 11–39). Heidelberg: Springer.

Ajzen, I. (2011). The theory of planned behavior: Reactions and reflections. *Psychology & Health, 26*(9), 1113–1127. https://doi.org/10.1080/08870446.2011.613995

Ajzen, I., & Fishbein, M. (1980). *Understanding attitudes and predicting social behavior*. Englewood Cliffs, NJ: Prentice-Hall.

Alba, J. W., & Hutchinson, J. W. (1987). Dimensions of consumer expertise. *Journal of Consumer Research, 13*(4), 411–454. https://doi.org/10.1086/209080

Alzhanova, F.G., Kireyeva, A. A., Satpayeva, Z. T. Tsoy, A. A., & Nurbatsin, A. (2020). Analysis of the level of technological development and digital readiness of scientific-research institutes. *The Journal of Asian Finance, Economics, and Business, 7*(12), 1133–1147. https://doi.org/10.13106/jafeb.2020.vol7.no12.1133

Davis, F. D., Bagozzi, R.P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science, 35*(8), 982–1003. https://doi.org/10.1287/mnsc.35.8.982

Flache, A., Mäs, M., Feliciani,T., Chattoe-Brown, E., Deffuant, G., Huet, S., & Lorenz, J. (2017). Models of social influence: Towards the next frontiers. *Journal of Artificial Societies and Social Simulation, 20*(4), 21–35. https://doi.org/10.18564/jasss.3521

Guo, Z., Yu, L., Wang, L., Bhattacharya, S., Nikitas, G., & Xing, Y. (2015). Model tests on the long-term dynamic performance of offshore wind turbines founded on monopiles in the sand. *Journal of Offshore Mechanics and Arctic Engineering*, *137*(4), 041902. https://doi.org/10.1115/1.4030682

Hair, J. F., Black, W. C., Babin, B.J., & Anderson, R. E. (2010). *Multivariate data analysis* (7th.ed.). Upper Saddle River, NJ: Pearson.

Hoyle, R. H. (2011). *Structural equation modeling for social and personality psychology*. London: Sage Publications Ltd.

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1–55. https://doi.org/10.1080/10705519909540118. hdl:2027.42/139911

Kline, R. B. (2015). *Principles and practice of structural equation modeling*. New York: Guilford Press.

Kohpaiboon, A. (2020). *Industry 4.0 policies in Thailand*. http://hdl.handle.net/11540/11693

Lee, J. W. (2020a). Big data strategies for government, society, and policy-making. *The Journal of Asian Finance, Economics, and Business, 7*(7), 475–487. https://doi.org/10.13106/jafeb.2020.vol7.no7.475

Lee, J. W. (2020b). The roles of online instructional facilitators and student performance of the online class activity. *The Journal of Asian Finance, Economics, and Business, 7*(8), 723–733. https://doi.org/10.13106/jafeb.2020.vol7.no8.723

Melitski, J., Gavin, D., & Gavin, J. (2010). Technology adoption and organizational culture in public organizations. *International Journal of Organization Theory & Behavior*, *13*(4), 546–568. http://doi.org/10.1108/IJOTB-13-04-2010-B005

Mergel, I., Edelmann, N., & Haug, N. (2019). Defining digital transformation: Results from expert interviews. *Government Information Quarterly*, *36*(4), 101385. https://doi.org/10.1016/j.giq.2019.06.002

Ministry of Industry. (2016). *National strategic development plan Thai 4.0*. http://www.oie.go.th/sites/default/files/attachments/industry_plan/thailandindustrialdevelopmentstrategy4.0.pdf

National Productivity Institute. (2018). *Thailand 4.0 country development model for sustainable, prosperous, and sustainable development.* From http://www.ftpi.or.th/ 2016

National Statistical Office. (2021). *Labor of the elderly in 2020 report*. http://www.nso.go.th/

Shonhe, L. (2019). An assessment of the technology readiness of public librarians in Botswana. *Global Knowledge, Memory, and Communication, 68*(4/5), 275–287. https://doi.org/10.1108/GKMC-10-2018-0086

Widagdo, P. P., & Susanto, T. D. (2016). The effect of task technology fit toward individual performance on the Generation X (1956–1980) using information technology. Science and Information Technology, *20*(16), 181–186. https://doi.org/10.1109/SITech.2016.7852630

Wolor, C. W., Solikhah, S., Fidhyallah, N. F., & Lestari, D. P. (2020). Effectiveness of e-training, e-leadership, and work-life balance on employee performance during COVID-19. *The Journal of Asian Finance, Economics, and Business, 7*(10), 443–450. https://doi.org/10.13106/jafeb.2020.vol7.no10.443

Yang, K. C., & Shih, P. H. (2020). Cognitive age in technology acceptance: At what age are people ready to adopt and continuously use fashionable products? *Telematics and Informatics, 51*, 101400. https://doi.org/10.1016/j.tele.2020.101400