

Study of Factors Influencing Digital Transformation Process in Bangkok

Sumas Wongsunopparat

Ph.D., Johnson Graduate School of Management, Cornell University, USA

MBA, Tepper School of Business, Carnegie Mellon University, USA

E-mail: dr.sumas62@gmail.com

Thusitha De Silva

Master of Business Administration, Bangkok University, Bangkok, Thailand

E-mail: thusitha.desi@bumail.net

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Abstract

Most digital transformations fail. Various studies from academics, consultants, and analysts indicate that the rate of digital transformations failing to meet their original objectives ranges from 70% to 95%, with an average at 87.5%. Yet, digital transformation has been at the top of corporate agendas for at least a decade and shows no sign of slowing down. On the contrary, many commentators have highlighted the accelerating impact of the Covid-19 period on digital transformation. Digital transformation is something no management team should attempt alone. It takes deep into reality and a sense of ownership among people across the enterprise to make transformation a reality.

The purpose of this research is to study factors influencing digital transformation process in Bangkok, Thailand. These factors include seven first-order independent variables: Leadership (LD), Employee (EP), Culture (CT), Work Environment (WE), Mindset (MS), Organizational Friction (OF), Management of Transformation (MT), and Talent Acquisition (TA); three second-order variables: Leadership & Motivation (LDM), People (PPL), and Workplace Culture (WPC) and one dependent variable: Digital Transformation (DT). 400 sample were

collected using electronic questionnaire through social media. We used Structural Equation Models (SEM) for data analysis. The result shows that since the RMSEA, which is an absolute fit index that assesses how far our hypothesized model is from a perfect model, for this model is .04 ($<.05$) which strongly indicates a “close fit” and the Goodness of Fit Index (GFI) value is .902 ($>.90$), the model seems to fit well according to the descriptive measures of fit. Moreover, CFI, which is incremental fit indices that compare the fit of our hypothesized model with that of a baseline model (i.e., a model with the worst fit), its value equals .903 indicating an acceptable fit.

More importantly, Talent Acquisition (TA), Leadership & Motivation (LDM), and Workplace Culture (WPC) seem to have significant effects on Digital Transformation (DT) process due to their p-values are all less than .05. That means if corporates focus more on acquiring new talent and at the same time improve corporate leadership and motivation and workplace culture, they will be more likely to be successful in digital transformation which is necessary condition for all organizations to be competitively sustainable going forward.

Keywords: digital transformation, SEM; talent acquisition, leadership & motivation, and workplace culture, Covid-19

1. Introduction

1.1 Background of the Study

Most digital transformations fail. Various studies from academics, consultants, and analysts indicate that the rate of digital transformations failing to meet their original objectives ranges from 70% to 95%, with an average at 87.5%. Yet, digital transformation has been at the top of corporate agendas for at least a decade and shows no sign of slowing down. On the contrary, many commentators have highlighted the accelerating impact of the Covid-19 period on digital transformation. Digital transformation is something no management team should attempt alone. It takes deep into reality and a sense of ownership among people across the enterprise to make transformation a reality.

Digital transformation refers to the process of integrating digital technologies into all aspects of a business or organization, with the goal of improving efficiency, effectiveness, and competitiveness. With the advent of the internet, mobile devices, cloud computing, and other digital tools, businesses and organizations have been able to automate processes, collect and analyze data more efficiently, and communicate with customers and stakeholders in new ways.

However, the digital transformation process is not without its challenges. Many organizations struggle to effectively integrate new technologies into their existing systems and processes and may face resistance from employees or other stakeholders who are hesitant to change established ways of doing things. In addition, there may be issues related to cybersecurity, data privacy, and regulatory compliance that must be addressed in the context of digital transformation.

1.2 Digital Transformation of Thailand

Thailand has been actively pursuing digital transformation initiatives in recent years, with a focus on leveraging digital technologies to drive economic growth, improve public services, and enhance overall competitiveness. Some key examples of digital transformation efforts in Thailand such as Digital Government, Smart Cities, Digital Economy, and Cyber security.

1.2.1 Digital Government

Thailand's Digital Government Development Agency (DGA) has been working to modernize government services and improve access to public information through digital channels. This includes the development of online portals for citizen services, such as e-tax filing, e-payment, and online business registration (Ark, 2020).

1.2.2 Smart Cities

Thailand has launched several smart city initiatives, aimed at using digital technologies to enhance urban living and address issues such as traffic congestion and air pollution. The city of Bangkok, for example, has launched a smart mobility project that includes real-time traffic monitoring, intelligent transportation systems, and mobile apps for public transportation (Phongsyok, 2019).

1.2.3 Digital Economy

Thailand has also been working to develop a thriving digital economy, with a focus on supporting entrepreneurship and innovation in areas such as e-commerce, fintech, and digital content. The government has established several digital innovation hubs, including the Digital Park Thailand and the Eastern Economic Corridor (EEC) project, which aims to create a high-tech industrial zone to attract foreign investment (Hutanuwatra, 2021).

1.2.4 Cybersecurity

Thailand has recognized the importance of cybersecurity in the context of digital transformation and has established a national cybersecurity agency to oversee the country's cybersecurity strategy. The government has also implemented various measures to improve cybersecurity, such as the Cybersecurity Act, which regulates the use of digital infrastructure and data protection (Srisa-an, 2018).

1.3 Statement of Problem

Digital transformation has become a critical aspect of business strategy in today's fast-paced and technology-driven environment. However, organizations face numerous challenges in the process of digitally transforming their operations, such as outdated legacy systems, resistance to change, lack of digital skills, and inadequate IT infrastructure. To successfully undertake digital transformation, it is essential to identify and understand the key factors that influence the process, including organizational culture, leadership support, employee engagement, data management, cybersecurity, and customer-centricity. Therefore, the problem statement for

this study is to investigate the factors that influence the digital transformation process of Thailand.

1.4 Literature Review

1.4.1 Technology Acceptance Model (TAM) Theory

The Technology Acceptance Model (TAM) Theory suggests that people are more likely to adopt new technologies when they perceive them as useful and easy to use. Venkatesh, Morris, Davis, and Davis (2003) explain that the TAM consists of two factors: perceived usefulness and perceived ease of use. They argue that these factors determine an individual's intention to use a technology.

Perceived usefulness (PU) is a key construct in the Technology Acceptance Model (TAM), which refers to the degree to which an individual believes that using a particular technology will enhance their job performance or overall productivity. The research studies of Davis (1989), Venkatesh, Morris, Davis, and Davis (2003), Moon & Kim (2001), Wu & Wang (2005) and Bhattacharjee (2001) provide empirical evidence that perceived usefulness is a significant determinant of technology adoption and usage. They also demonstrate the utility of the PU construct in a variety of technological contexts, such as the world-wide-web, mobile commerce, and information systems. Furthermore, these studies suggest that factors such as confirmation, expectation, and social influence may influence the perceived usefulness of a technology.

Perceived ease of use (PEOU) is another key construct in the Technology Acceptance Model (TAM), which refers to the degree to which an individual believes that using a particular technology will be free of effort. The research studies of Davis (1989), Venkatesh, Morris, Davis, and Davis (2003), Liaw & Huang (2013), Kim, Lee & Lee (2013), and Yi, Jackson, Park & Probst (2006) provide empirical evidence that perceived ease of use is a significant determinant of technology adoption and usage. They also demonstrate the utility of the PEOU construct in a variety of technological contexts, such as mobile payment and information technology adoption by professionals. Furthermore, these studies suggest that factors such as social influence, perceived risk, and trust may influence the perceived ease of use of a technology.

1.4.2 Resource-Based View (RBV) Theory

The Resource-Based View (RBV) is a theoretical framework that explains how firms can achieve sustainable competitive advantage by utilizing and developing their unique resources and capabilities. RBV suggests that a firm's competitive advantage depends on its internal resources and capabilities, which are difficult to imitate or replicate by competitors. In this way, firms can sustain their competitive advantage in the long run.

One of the key researchers in the development of RBV was Jay Barney. In his article "Firm Resources and Sustained Competitive Advantage" (1991), he proposed that a firm's resources must meet four criteria to be a source of sustained competitive advantage:

Valuable: resources must enable the firm to exploit opportunities or reduce threats in its environment.

Rare: resources must be unique or at least rare in the industry.

Inimitable: competitors should not be able to imitate the resource or capability easily.

Non-substitutable: there should not be any alternative resources or capabilities that can replace the valuable, rare, and inimitable resource or capability.

Another researcher who contributed to the development of RBV is Birger Wernerfelt. In his article "A Resource-Based View of the Firm" (1984), he argued that a firm's resources and capabilities can be organized into a bundle of strategic assets that determine its competitive position in the industry.

RBV has been applied in various fields, including strategic management, international business, and entrepreneurship. For example, researchers have used RBV to explain why some firms are more successful than others in international markets (Liu & Li, 2018) and to identify the key resources and capabilities that enable entrepreneurs to create successful startups (Barney & Clark, 2007).

1.4.3 The Disruptive Innovation Theory

The Disruptive Innovation Theory is originally introduced by Clayton Christensen in his book "The Innovator's Dilemma" in 1997, is a concept that explains how smaller, less-established companies can challenge and eventually displace established market leaders through the introduction of disruptive technologies or business models. The theory has been influential in the field of innovation and strategic management. The key elements of Disruptive Innovation theory are as follows:

Definition of Disruptive Innovation:

Disruptive innovation refers to the process by which a new product or service initially caters to a niche market or a less-demanding customer segment but eventually gains mainstream acceptance, challenging and displacing existing products or services. The disruptive innovation theory identifies two types of innovations: sustaining innovations, which improve existing products for established customers, and disruptive innovations, which create new markets by targeting non-consumers or low-end customers (Christensen C. M., 1997).

Characteristics of Disruptive Innovations:

Disruptive innovations typically possess certain characteristics, including simpler, more affordable, and more accessible designs compared to established products. They often target underserved customer segments or non-consumers and offer different value propositions that are initially considered inferior by the mainstream market. Over time, disruptive innovations improve and eventually outperform existing products, capturing larger market shares (Christensen, Raynor, & McDonald, 2015).

Disruption and Incumbent Responses:

The theory suggests that incumbent companies, focused on sustaining innovations and serving their existing customers, tend to overlook or dismiss disruptive technologies or business models that initially offer lower performance. As a result, incumbents often fail to respond adequately to disruptive threats, allowing disruptors to gain a foothold and eventually disrupt the market. Incumbents may also face challenges in embracing disruptive innovations due to conflicting business models and resource allocation (Bower & Christensen, 1995).

The Innovator's Dilemma:

The theory introduces the concept of the "innovator's dilemma," which explains why successful companies can fail to adapt to disruptive innovations. Established companies often face the dilemma of investing in sustaining innovations to meet the needs of existing customers or allocating resources to disruptive innovations that may initially provide lower returns. The focus on sustaining innovations can lead to a blind spot for disruptive threats and hinder the ability to respond effectively (Christensen C. M., 1997).

Application and Examples:

The disruptive innovation theory has been applied to various industries and sectors, including technology, manufacturing, healthcare, and finance. Examples of disruptive innovations include the personal computer, digital photography, online streaming services, and ridesharing platforms. These disruptive innovations fundamentally transformed their respective industries and displaced established companies that failed to anticipate or respond to the disruptive forces (Zott, Amit, & Massa, 2011).

1.4.4 Dynamic Capabilities Theory

Dynamic capabilities theory refers to the ability of organizations to integrate, build, and reconfigure their internal and external resources to adapt to changes in the environment and sustain competitive advantage. This theory was first introduced by Teece, Pisano, and Shuen (1997) and has since been expanded upon by numerous scholars.

One key aspect of dynamic capabilities theory is the notion of resource reconfiguration. This refers to the ability of firms to transform their resources and capabilities in response to changes in the environment, such as shifting consumer preferences, technological advances, or changes in industry regulation.

Another important aspect of dynamic capabilities theory is the role of knowledge creation and learning. Organizations that are able to continually learn and generate new knowledge are better equipped to adapt to changing environments and sustain competitive advantage.

Dynamic capabilities theory has been applied in a wide range of contexts, from high-tech industries to traditional manufacturing. For example, in the automotive industry, dynamic capabilities have been used to develop new electric and hybrid powertrains in response to

changing consumer preferences and stricter emissions regulations (Liu et al., 2021).

1.5 Related Literature

1.5.1 Effect of Talent Acquisition on Digital Transformation

Talent acquisition is the process of attracting, identifying, and hiring skilled and talented individuals to meet the needs of an organization. It is a critical aspect of digital transformation because it enables organizations to acquire the necessary human capital to implement technological changes and innovation. In this response, I will discuss the effect of talent acquisition on digital transformation, supported by relevant references from academic literature.

One of the most significant impacts of talent acquisition on digital transformation is the acquisition of individuals with specialized skills and knowledge. According to De Hauw et al. (2018), organizations that are successful in digital transformation recruit individuals with technical, data analytics, and digital marketing skills. These individuals can help organizations develop and implement digital strategies that enable them to leverage new technologies, processes, and models. By hiring individuals with these skills, organizations can create a workforce that is capable of delivering digital initiatives that align with their strategic objectives.

Another effect of talent acquisition on digital transformation is the creation of a culture that supports innovation and agility. According to PwC (2020), organizations that are successful in digital transformation have a culture that encourages experimentation, risk-taking, and learning from failure. Talent acquisition can play a crucial role in creating this culture by identifying and hiring individuals who are open to new ideas and approaches. These individuals can bring fresh perspectives and innovative ideas that can help organizations transform their processes and services.

Moreover, talent acquisition can help organizations build diverse and inclusive teams that can drive digital transformation. According to McKinsey (2020), diverse teams are more likely to generate creative and innovative solutions. They can also help organizations better understand the needs and preferences of their customers and stakeholders, enabling them to deliver digital services that meet their expectations. By hiring individuals with diverse backgrounds and perspectives, organizations can create a workforce that reflects the communities they serve.

1.5.2 Effect of Leadership Management on Digital Transformation

Digital transformation is the process of using digital technologies to fundamentally change how an organization operates and delivers value to customers. Effective leadership and motivation are crucial for the success of digital transformation initiatives.

Leadership plays a critical role in shaping the vision, strategy, and implementation of digital transformation efforts. Leaders must provide clear guidance on how digital technologies can

enable the organization to achieve its strategic objectives. They must also communicate the benefits of digital transformation to employees, customers, and stakeholders, and build a culture that supports digital innovation and experimentation.

Motivation is equally important in driving digital transformation. Employees must be motivated to adopt new technologies and processes, and to embrace the changes that come with digital transformation. Motivation can be achieved through a variety of mechanisms, including incentives, training and development programs, and supportive leadership.

Research has shown that effective leadership and motivation are key drivers of successful digital transformation initiatives. A study by Deloitte (2017) found that organizations with strong digital leadership were nearly twice as likely to have successful digital transformation initiatives compared to those with weak digital leadership. Another study by MIT Sloan Management Review (2020) found that organizations with a strong focus on employee motivation were more likely to achieve their digital transformation goals.

1.5.3 Effect of People on Digital Transformation

Digital transformation is a process that involves the integration of digital technology into all areas of an organization, resulting in fundamental changes to how businesses operate and deliver value to their customers. However, the success of digital transformation initiatives depends on several factors, one of which is the role of people in the process.

Studies have shown that people are crucial to the success of digital transformation initiatives. In particular, the attitudes, skills, and behaviors of employees can have a significant impact on the adoption and implementation of digital technologies within an organization. For example, a study by McKinsey & Company (2018) found that organizations that prioritized the development of digital skills among their employees were more likely to succeed in their digital transformation efforts.

Similarly, a study by MIT Sloan Management Review found that companies that had a strong digital culture - one that encouraged experimentation, innovation, and risk-taking - were more likely to achieve digital transformation success. The study also found that companies that invested in employee training and development, and created a supportive environment for digital innovation, were more likely to achieve successful digital transformation.

Another critical factor in the success of digital transformation is the leadership's commitment to the process. Leaders must provide a clear vision for digital transformation and communicate the benefits to employees to gain their buy-in. In addition, leaders must prioritize digital initiatives, allocate the necessary resources, and hold themselves accountable for the success of the process.

1.5.4 Effect of Workplace Culture on Digital Transformation

Workplace culture can have a significant impact on the success of digital transformation initiatives within an organization. A positive culture that encourages collaboration,

experimentation, and innovation can help drive adoption of new technologies and processes. Conversely, a negative or stagnant culture can hinder progress and lead to resistance to change.

Research by Deloitte (2017) found that culture was a key factor in the success of digital transformation efforts, with 87% of respondents saying that culture was important or very important. In addition, organizations with a strong culture of innovation were found to be 3.5 times more likely to be high performers in digital transformation.

Another study by MIT Sloan Management Review and Deloitte found that cultural factors, such as a willingness to experiment and a focus on customer experience, were more important predictors of digital transformation success than technology factors. The study also highlighted the importance of leadership in shaping culture and driving change.

A Harvard Business Review article (2017) suggests that a culture of experimentation is essential for digital transformation, allowing organizations to test and iterate on new ideas quickly. The article notes that this type of culture requires leaders to create an environment that encourages risk-taking and learning from failure.

1.6 Hypothesis

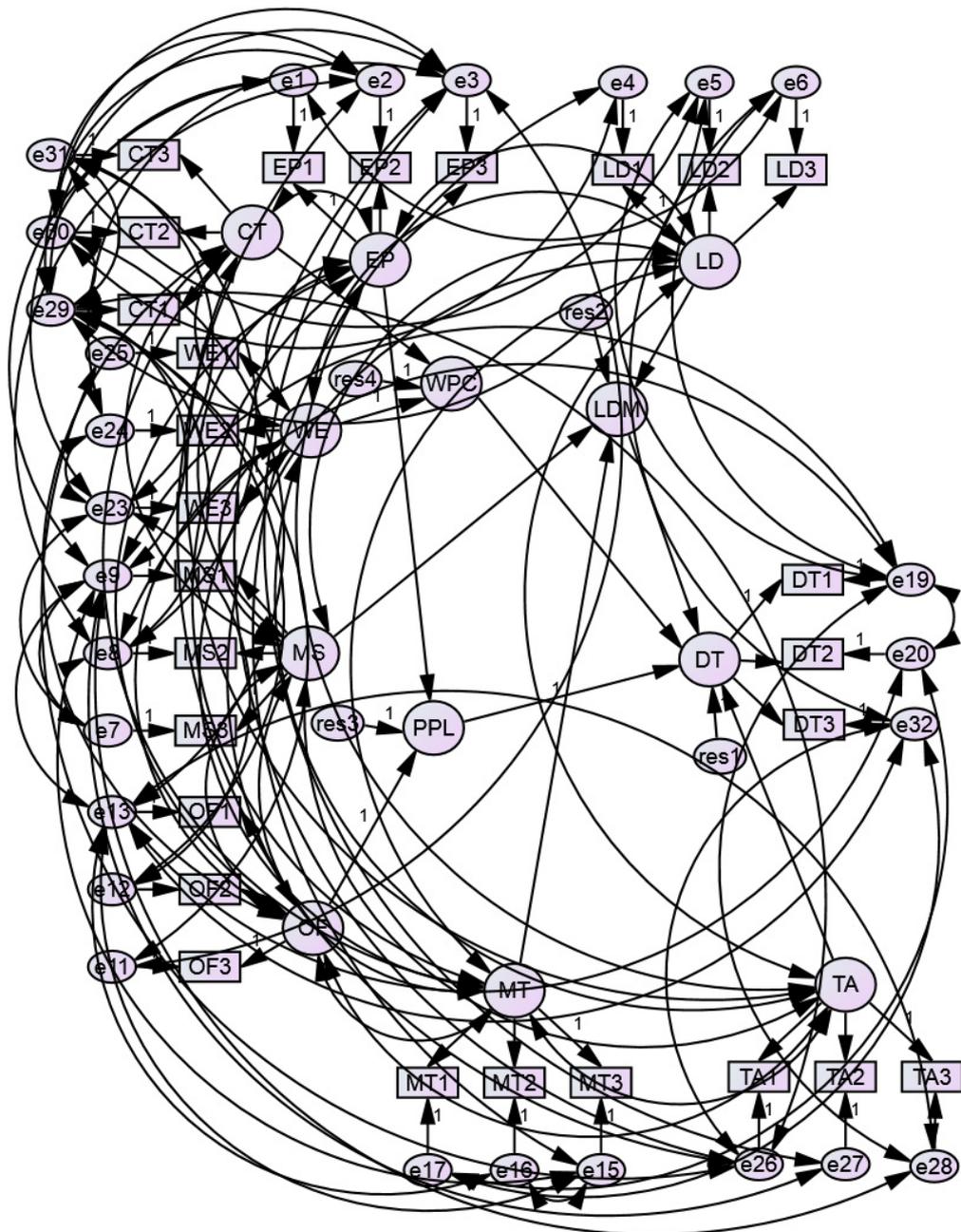
H1: Talent Acquisition will have the effect on Digital Transformation Process.

H2: Leadership Management will have the effect on Digital Transformation Process.

H3: People will have the effect on Digital Transformation Process.

H4: Workplace Culture will have the effect on Digital Transformation Process.

The Hypothesized Model



First-order variables: Leadership (LD), Employee (EP), Culture (CT), Work Environment (WE), Mindset (MS), Organizational Friction (OF), Management of Transformation (MT), Talent Acquisition (TA), Digital Transformation (DT)

Second-order variables: Leadership & Motivation (LDM), People (PPL), Workplace Culture (WPC)

2. Research Methodology

2.1 Research Strategy

In this study, a quantitative research method was employed to achieve the research objectives, which was to investigate the factors that influence consumers' adoption of Electric Vehicles. The researcher utilized questionnaires as a survey tool to collect and analyze data. The questionnaire was constructed based on relevant theories and approved by experts.

Quantitative research methods can be categorized into three types: descriptive, experimental, and casual comparative. This study adopted a casual comparative approach, which focuses on examining how the independent variables affect the dependent variable as part of cause-and-effect relationships, with a particular emphasis on the interaction between independent variables and the dependent variable (Williams, 2007).

The research sample was carefully selected from the population using a combination of convenient and purposive sampling methods. Inferential statistics, descriptive statistics, and Structural Equation Modelling (SEM) for Factor Analysis were the statistical techniques used for data analysis and interpretation.

2.2 Reliability

The value of Cronbach's alpha coefficient is using by the researcher to measure the reliability of the Questionnaire. The researcher was performed 30 peoples as a sample for the pilot test and afterward enter the data into IBM SPSS 23 statistical software. The questionnaire's Cronbach's alpha coefficient must be more than 0.70 for all portions in order for it to be judged reliable (Taber, 2018).

Criteria of Cronbach's alpha coefficient

Cronbach's alpha coefficient	Reliability Level	Desirability Level
0.80 – 1.00	Very High	Excellent
0.70 – 0.79	High	Good
0.50 – 0.69	Medium	Fair
0.30 – 0.49	Low	Poor
Less than 0.30	Very Low	Unacceptable

The result of Cronbach's Alpha Test from 30 samples: All Factors

Statement of each part	Alpha Coefficient	Accepted/ Not
Leadership	0.814	Accepted
Employee	0.893	Accepted
Culture	0.827	Accepted
Work Environment	0.875	Accepted
Mindset	0.905	Accepted
Organizational Friction	0.921	Accepted
Management of Transformation	0.915	Accepted
Talent Acquisition	0.857	Accepted
Leadership & Motivation	0.864	Accepted
People	0.806	Accepted
Workplace Culture	0.902	Accepted
Digital Transformation	0.925	Accepted
All Factors	0.882	Accepted

2.3 Target Population and Sample Size

2.3.1. Population

Population can be described as the people who lived in Bangkok, Thailand. The target population including the native and foreigners who live, work and study in Bangkok not lower than 1 year.

2.3.2 Sample Size

Structural Equation Modeling (SEM) is a powerful and versatile technique that extends the generic linear model. Like other statistical methods, SEM has a set of assumptions that must be met or approximated to ensure accurate results. One of the main challenges in SEM is determining the appropriate sample size, which unfortunately has no general method for selection.

Bentler and Chou (1987) suggest that researchers use at least 5 examples for each parameter estimate in SEM analysis, assuming that the data is well-behaved (e.g., no missing data, normally distributed, etc.). Additionally, they recommend that researchers use 5 cases per parameter estimate instead of every observed variable. Since measured variables usually have at least one path coefficient related to another variable in the analysis, as well as a residual term or variance estimate, it is important to follow the recommendations of Bentler, Chou,

and Stevens and have a minimum of 15 cases per measured variable. Most of the researchers are recommended to using the sample size of 200 or 5/10 cases per parameters at least (Kline, 2005).

Moreover, the outcomes of the simulation of Monte Carlo which is studying the use of confirmatory factor analysis models (Loehlin, 1992). After assessing his literature, he realizes that for this kind of model with 2 to 4 factors, the researchers should have a plan on collecting at 100 cases minimum, 200 cases is better (if possible). Consequences of using the smaller samples contain of more convergence failures (the software cannot make a acceptable solution), lowered precision of parameter estimates, inappropriate solutions (together with the negative error variance estimates for measured variables), and especially, standard errors – SEM program standard errors are computed under the assumption of large sample sizes.

However, higher sample sizes are required when the data is not normally distributed or is otherwise defective in some way (nearly usually the case). When the data is skewed, partial, kurtotic, or otherwise less than perfect, it is difficult to provide complete recommendations for sample sizes. When possible, it is generally advised to collect additional data. Although in this research study is using 400 samples. The 400-sample size is often considered as the most “cost effective” sample size and it gives the statistical accuracy of $\pm 5\%$.

3. Research Findings

3.1 Factor loading and Rotated Matrix

KMO and Bartlett's Test	
KMO	.910
Chi-Square	11863.800
Df	435
Sig	.000

According to the results of Kaiser-Meyer-Olkin (KMO) test and the Bartlett's test of sphericity of the above table, KMO of 0.910 (greater than 0.80) and significance of the Bartlett's test of sphericity showed that the data were appropriate for factor analysis.

Table title

Rotated Component Matrix^a				
	Component			
	1 LDM Leadership & Motivation	2 PPL People	3 WPC Workplace Culture	4 TA Talent Acquisition
LD1	.707	.100	.330	.230
LD2	.673	.336	.133	.297
LD3	.248	.683	.193	.167
EP1	.335	.763	.011	.318
EP2	.140	.450	.161	.690
EP3	.567	.283	.007	.455
CT1	.207	.355	.617	.425
CT2	.571	.217	.503	.271
CT3	.429	.273	.492	.391
WE1	.343	.250	.769	.092
WE2	.334	.419	.714	-.025
WE3	.171	-.011	.775	.320
MS1	.291	.645	.336	.339
MS2	.676	.413	.232	.241
MS3	.632	.419	.209	.286
OF1	.371	.624	.362	.184
OF2	.138	.126	.468	.462
OF3	.733	.277	.244	.193
MT1	.676	.387	.209	.078
MT2	.729	.283	.210	.228
MT3	.744	.087	.358	.239
TA1	.355	.196	.284	.722
TA2	.447	.276	.275	.585
TA3	.506	.159	.199	.663
DT1	.570	.440	.276	.246
DT2	.554	.550	.291	.200
DT3	.602	.316	.317	.466

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 9 iterations.

The above table presents the results of a Principal Component Analysis (PCA) with Varimax rotation and Kaiser normalization. The analysis aimed to identify the underlying factors or components of a set of variables related to Leadership & Motivation, People, Workplace Culture, Talent Acquisition, and Digital Transformation.

The table shows the Rotated Component Matrix, which displays the correlations between the variables and the extracted components after rotation. Each row represents a variable, and each column represents a component. The values in the table represent the factor loadings, which indicate the correlation between a variable and a component.

3.2 Correlation of the Variables

This section reviews the various goodness-of-fit criteria for testing the model in the following

manner. Model evaluation uses root mean square residuals (RMR) as one of the review criteria, and a model is considered good or satisfactory if the RMR value is low. RMR is the root mean square of the residuals. RMR is the sum of the squares of the sample variances and covariances minus the corresponding estimated variances and covariances, and the square root of the mean. RMR is acceptable if it is less than 0.08. The smaller the RMR, the better the fit the smaller the RMR, the higher the goodness of fit. The goodness-of-fit index (GFI) is a measure of goodness-of-fit that ranges from 0 to 1 but can theoretically be a negative number with no significance. By convention, the GFI should be equal to or greater than 0.90 for the model to be considered acceptable. The adjusted goodness-of-fit index (AGFI) is the adjusted GFI value and should be greater than 0.9 or more for the model to be considered acceptable. Parsimonious normed fit index (PGFI) determines whether the research model is too complex, and the same sample information but similar models are better with a larger parsimonious index. Usually PGFI >0.50, the model is considered satisfactory.

SEM Result

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	.040	.902	.800	.450

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.870	.771	.900	.808	.903

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.04	.038	.047	.755

Since the RMSEA, which is an absolute fit index that assesses how far our hypothesized model is from a perfect model, for this model is .04 (<.05) which strongly indicates a “close fit” and the Goodness of Fit Index (GFI) value is .902 (>.90), the model seems to fit well according to the descriptive measures of fit. Moreover, CFI, which is incremental fit indices that compare the fit of our hypothesized model with that of a baseline model (i.e., a model with the worst fit), its value equals .903 indicating an acceptable fit.

3.3 Hypothesis Result

Regression Weights: (Group number 1 - Default model)

	Estimate	S.E.	C.R.	P	Label
DT <--- TA	.193	.024	7.940	***	
DT <--- LDM	.260	.037	7.020	***	
DT <--- PPL	.003	.033	.079	.937	
DT <--- WPC	.067	.025	2.635	.008	

Talent Acquisition (TA), Leadership & Motivation (LDM), and Workplace Culture (WPC) seem to have significant effects on Digital Transformation (DT) process due to their p-values are all less than .05.

4. Conclusion

4.1 Discussion on Hypothesis Result

H1: Talent Acquisition have the effect on Digital Transformation Process.

H2: Leadership Management have the effect on Digital Transformation Process.

H3: People do not have the effect on Digital Transformation Process.

H4: Workplace Culture have the effect on Digital Transformation Process.

According to our SEM result, Talent Acquisition (TA), Leadership & Motivation (LDM), and Workplace Culture (WPC) seem to have significant effects on Digital Transformation (DT) process due to their p-values are all less than .05. That means if corporates focus more on acquiring new talent and at the same time improve corporate leadership and motivation and workplace culture, they will be more likely to be successful in digital transformation which is necessary condition for all organizations to be sustainable going forward.

4.2 Conclusion

Talent acquisition is a critical aspect of digital transformation that enables organizations to acquire the necessary human capital to implement technological changes and innovation. By hiring individuals with specialized skills and knowledge, creating a culture that supports innovation and agility, and building diverse and inclusive teams, organizations can transform their processes and services and remain competitive in the digital age.

Much Research were shown that effective leadership and motivation are key drivers of

successful digital transformation initiatives. A study by Deloitte found that organizations with strong digital leadership were nearly twice as likely to have successful digital transformation initiatives compared to those with weak digital leadership. Another study by MIT Sloan Management Review found that organizations with a strong focus on employee motivation were more likely to achieve their digital transformation goals.

People are an essential factor in the success of digital transformation initiatives. Organizations must prioritize the development of digital skills, create a supportive digital culture, and provide strong leadership to ensure the successful adoption and implementation of digital technologies. However the current research is contrary to previous researches which means that people are no longer essential factor to success of Digital Transformation process in Bangkok.

Overall, the evidence suggests that workplace culture plays a crucial role in digital transformation success. By fostering a positive, innovative culture that embraces change and experimentation, organizations can better position themselves to succeed in the digital age.

4.3 Recommendations for Future Research

The generalizability of the findings are the limitations of this study. The sample used in this research was targeted on all age groups. So that future research should be choosing the certain age groups. The different viewpoints of confirmatory factor analysis (CFA) can also be applied on the factors which were reviewed in this research to find further inside on the Study of Factors Influencing Digital Transformation Process in Bangkok. Moreover, the different Structural construct and model can be used based on the factors discussed in the paper.

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