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The Impact of IT Knowledge Capability and Big Data and Analytics on Firm's Industry 4.0 Capability †

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Abstract: Smart factory is a fully-integrated of firm's facilities (i.e., sensors, smart machines, and robots) and information system architecture (i.e., IoT, ICT, and cloud computing) to enable high degree of automation in manufacturing processes. IT knowledge capability is the IT knowledge organization that how employees understand IT knowledge in different dimensions, i.e., general management, product design, production planning, data analysis, information security, and automation system. Since the system of smart factory depends on the massive of data collecting (big data) and the firm's advance analyzing approach (analytics). The big data in manufacturing include the data from production planning, quality control, procurement, inventory control, human resource management (HRM), and delivery. The purpose of this study is to examine the role of IT knowledge capability and big data and analytics on the degree of smart factory. Survey data from 141 Thai manufacturing firms from the list of the ministry of industry and industrial zones were collected during March–April 2019. The multiple regression result shows that both IT knowledge capability and big data and analytics have a positive impact on the degree of smart factory. In addition, we use a firm's age and firm's size (based on the number of employees and total asset) as control variables. The results show that firm's size have a positive effect on hypothesis model.

Keywords: Industry 4.0; smart factory; IT knowledge capability; big data and analytics

1. Introduction

The revolution of Industry 4.0 is the extension of advance technologies to connect manufacturing production systems due to the integration of machines, information communication technology (ICT), internet of things (IoT), and cloud computing in Cyber-physical systems (CPS) [1,2]. CPS enables real-time-capable to connect people and machine along a horizontal and vertical manufacturing processes [3]. Advance technologies aim to improve the production systems to produce customization products in a large quantity. Thus, the implication these advance digital technologies is a big challenge for manufacturing companies, especially SMEs [4]. The previous studies on the contribution of Industry 4.0 technologies found that the challenge of upgrading technologies are included the high investment costs, lack of Industry 4.0 knowledge, lack of expertise, and low level of Industry 4.0 implementation [1,5]. Industry 4.0 in Thailand are increase in requirement of training employee about digitalization and automation skills. Hence, this study aims to examine (1) the role of IT knowledge capability on the degree of smart factory; and (2) the role of big data and analytics on the degree of smart factory.

2. Literature Review

Smart factory is a core of Industrial 4.0 revolution, which the machines and systems integrate by technology such as ICT, IoT, and cloud computing to enhance the automation steps in manufacturing processes [6]. In this study, smart factory is determined facilitating the automated, flexible and efficient production of the products and services [7]. The previous research demonstrated that the inclusion of big data and related technologies aim to increase the performance of various applications in smart factories, e.g., integrated platforms, visualization, and predictive analytics [8]. Hence, this study focus on two dimensions: (1) IT knowledge capability; (2) Big data and analytics.

For IT knowledge capability, it has defined as the ability to integrate and deploy knowledge by using information communication technology (ICT) effectively [9]. In this study, IT knowledge capability is conducted as the level of IT knowledge in each management level (i.e., shop floor level, production management level, and corporate management level).

Hypothesis 1. *IT knowledge capability has a positive effect on the degree of Smart Factory.*

To generate the digital twins of the factory, big data and analytics are required as the fundamental to enables advanced predicting and identifying events that can affect production before it happens [10]. This study considers big data and analytics as the effectiveness level of ICT data accumulated, ICT information sharing, and implementation to assist the automation processes.

Hypothesis 2. *Big data and analytics has a positive effect on the degree of Smart Factory.*

3. Methodology

A questionnaire-based research collected data during March–April 2019 from Thai Manufacturing Industry. The questionnaires were designed for establishment's manager or involving person to respond the question relating to Industry 4.0. There are 19-items of indicators, which categories as shown in Table 1. The dependent variable is the degree of smart factory, which include 4-indicators of a score value from 0 to 3 (0 = No, 1 = Little, 2 = Somewhat, 3 = Much). There are two independent variables. First, IT knowledge capability is indicated by 6-indicators of a 5-point Likert scale score values from 0 (Not sufficient) to 4 (Sufficient). Second, big data and analytics is indicated by 6-indicators of a score values from 0 (Not Practicing) to 4 (Very effectively). Moreover, we adopted three control variables to the hypotheses model, which are: (1) Firm's age; (2) Firm's size based on the number of employees; and (3) Firm's size based on total asset. Firm's size was classified to be a small firm, a medium firm, and a large firm. Previous research has shown that these variables can affect the development of technology and innovation [11].

The completed questionnaire papers that were enlisted and sent via Industrial Estate Authority of Thailand and Thai Auto parts Manufacturers Association. A total of 141 samples is adopted to multiple regression analysis to test the hypothesizes. Based on the number of employees, the respondents were the small firms of 47%, the medium firms of 38%, and the large firm of 15%. Based on total asset, the respondents were the small firms of 50%, the large firms of 29%, and the medium firms of 21%.

4. Result and Discussion

4.1. Reliability Test and Factor Analysis

A principal components factor analysis (CFA) was applied on 16-indicators to conduct 3 variables. The Kaiser-Meyer-Olkin (KMO), a measure of sampling adequacy, is suppressed small coefficients defining absolute value below 0.50 and assessed KMO value if it is more than 0.60 [12]. Then, Cronbach's alpha (α) coefficient is applied to check reliability of internal consistency of components. Cronbach's alpha was considered to evaluate how consistent both dependent and independent variables are. This test was specified alpha that should be more than 0.70 [13]. After

CFA was conducted, a Pearson product-moment correlation coefficient was applied to check multicollinearity between variables. All variables are accepted as show in the Table 1.

Table 1. Reliability test and factor analysis.

Variable	Mean	S.D.	Factor Loading
Degree of smart factory (KMO = 0.800, α = 0.812)			
1. Degree of automation in quality inspection process	1.48	0.789	0.792
2. Degree of automation in delivery and warehousing	1.31	0.887	0.760
3. Degree of automation in controlling system	1.50	0.875	0.814
4. Degree of automation in production process	1.41	0.793	0.840
IT knowledge capability (KMO = 0.894, α = 0.924)			
1. IT personal in general	2.48	1.080	0.702
2. IT system planning	2.31	1.153	0.883
3. IT system design	2.23	1.136	0.882
4. Data analysis	2.39	1.068	0.889
5. Information security	2.42	1.129	0.883
6. Factory automation	2.23	1.246	0.869
Big data and analytics (KMO = 0.865, α = 0.924)			
1. Data from production planning	1.94	0.904	0.750
2. Data from quality control	2.06	0.916	0.750
3. Data from procurement	2.01	0.853	0.801
4. Data from inventory control	2.24	0.810	0.756
5. Data from HRM	2.16	0.848	0.747
6. Data from delivery	1.86	0.953	0.645

4.2. Test of Hypothesis

This research has used multiple regression method by SPSS. The results of multiple regression analysis show a significant of hypothesizes with F-test value of 21.417 and adjust R^2 of 0.507, which accepted according to the measurement from [13]. For Hypothesis 1, IT knowledge capability was significant (b = 0.273, sig. = 0.002) which means IT knowledge capability has positive effect on degree of smart factory. The result is consistent with previous study that the develop of Industry 4.0 technologies and its implementation require the expertise or high skill employee [5,14]. For Hypothesis 2, big data and analytics was significant (b = 0.309, sig. = 0.000) which means Big data and analytics has positive effect on degree of smart factory. The result is compatible with previous study of industry 4.0 maturity index that big data and analytics important for predicting and decision-making processes [10]. Only two control variables were significant: (1) Large firm based on the number of employees (b = 0.235, sig. = 0.012), and (2) Large firm based on total asset (b = 0.135, sig. = 0.056). This indicate that the small and medium factories have a limit of human resources and financial support to upgrade and implement advance technology. This is consistent with previous study predicting this negative relationship [2]. However, the study of Saemundsson and Dahlstrand [15] found that firm's age plays an important on the probability to extend firm's capability and size. The results of multiple regression analysis present in Table 2.

Table 2. Result of multiple regression analysis on hypothesized.

Variable	F-Test	t-Test	Beta	Adjust R^2	Conclusion
Dependent variable					
Degree of smart factory	21.417 **			0.507	
Independent variables					
IT knowledge capability		3.215 **	0.273		Support
Big data and analytics		3.846 **	0.309		Support
Control Variables					
Firm's age		−0.089	−0.006		Not Support
Medium firm based on the number of employees		0.005	0.000		Not Support
Large firm based on the number of employees		2.562 **	0.235		Support
Medium firm based on total asset		1.315	0.090		Not Support
Large firm based on total asset		1.926 *	0.135		Support

Note: ** Significant at 0.01 level, * Significant at 0.05 level.

5. Conclusions

This research aims to explore the role of IT knowledge capability and big data and analytics on the degree of smart factory. We conducted a survey on manufacturing industry in Thailand. The result showed that TI knowledge capability and big data and analytics are positively influence on the degree of smart factory. Most of establishments have attempted to utilize machines, facilities and equipment based on ICT knowledge to improve their productivity. In conclusion, the level quality of IT employees has an important role to develop the quality inspection and inventory management. It is also implied that machine and automation system were manipulated by highly-skilled IT employees [6]. The ICT data collecting and sharing in factory and capacity of analyzing with advance techniques are enabled the advance application of technologies. Thus, firms can achieve higher degree of automation processes establishments.

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