A Study on the Relationship between Investment in Education and Training and Smart Factory Level of Manufacturing SMEs

By

OH, Meehyeun

THESIS

Submitted to

KDI School of Public Policy and Management

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For the Degree of

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ABSTRACT

A STUDY ON THE RELATIONSHIP BETWEEN INVESTMENT IN EDUCATION AND TRAINING AND SMART FACTORY LEVEL OF MANUFACTURING SMEs

By

Oh, Meehyeun

Smart Factories so far have achieved quantitative growth led by the government, but discussions are insufficient on how to promote the qualitative advancement of the supplied Smart Factory. This paper performs a binomial logistic regression to find the determinants of the level of Smart Factories focused on the investment of education and training by using the 2019 Workplace Panel Survey data of the Korea Labor Institute (KLI). The analysis results of the study show that the existence of a person (department) in charge, the pre-planning establishment, the annual average of training hours per person, the ratio of training participation, and training cost per person were not significant determinants of the level of Smart Factories. The main training contents seem to have a positive effect on the level of Smart Factories.

Key Words: Level of Smart Factories, Investment in Education and Training, Manufacturing SMEs

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The journey of life in KDI school was a big challenge for me.

It could be just one of the slopes in the merry-go-round of my life,

but I believe those times will be the strength to support me.

Painful memories can be glorified and only shining memories will remain.

Anyhow it was a long, long trip for me.

Thankful to those who helped me whenever I was tired and struggling.

Thank you so much to my husband, family, professor Lee Changkeun, professor Yoon Chungeun, friends, and team members.

And I give enthusiastic applause to myself.

Have a soulful day both in mind and body.

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I. INTRODUCTION

Smart Factories are now considered an innovation strategy and a key element for strengthening the competitiveness of domestic manufacturing companies. Korean government set the proliferation of Smart Factories as its major project for fostering small and mid-sized manufacturing companies to keep their competitiveness in the digital-transforming era.

The Ministry of SMEs and Startups (MSS), demonstrates the quantitative expansion of Smart Factories as the number of factories that build in one year surged from 227 in 2014 to 7,139 in 2020, recording a cumulative number of 19,799 from 2014 to 2020. Among them, the machinery industry had the highest portion (17.2%), the automobile parts industry (15.4%), and the metal processing industry (11.1%) followed.

Also, the Korea Institute for Industrial Economics and Trade (KIET)'s report for performance analysis of the adoption of Smart Factory ('14~'18, 7,903 companies) indicated that companies that established Smart Factory have improved their production competitiveness by raising productivity by 28.5%, enhancing the quality of products in 42.5%, reducing production cost for 15.5% in average. Furthermore, it showed that those companies' business performances improved by hiring 2.6 more employees, increasing by 7.4% more profit and declining industrial accidents by 16.2%. With these positive results, the Korean government planned to encourage businesses to build 5,000 Smart Factories (see, e.g., MSS, 2022).

However, despite the quantitative expansion of Smart Factories, many companies have had difficulties properly using the factories (see, e.g., Kim H., & Ji I., 2020; Park J., & Kang J., 2020; Kang J, & Cho K., 2018). For example, according to the MSS, most Smart Factories are at a lower level and they tend to focus on replacing facilities or installing solutions rather than trying to improve their smart production innovation competency. As such the introduction of Smart Factories so far has achieved 'quantitative growth' led by the government, but discussions are insufficient on how to promote the 'qualitative advancement' of the supplied Smart Factory.

Thus, this paper aims to determine whether the characteristics of education and training are factors that determine the level of Smart Factories by using the 2019 Workplace Panel Survey data of the Korea Labor Institute (KLI).

II. LITERATURE REVIEW

2.1 Smart Factory

What is a Smart Factory? The definition of Smart Factories is discussed in various meanings and contexts, and the standards for Smart Factories defined by countries, government ministries, and companies are also different. Due to the complexity and diversity of planning, design, manufacturing, process, distribution, and sales, it is particularly difficult to define a Smart Factory. For example, Germany, the cradle of the concept of Smart Factories, defined a Smart Factory as the "Digitization and networking of all processes, products, and resources" as written by Chung, S. et al. (2019). In addition, Table 1 shows the definition of Smart Factories defined by each institution, such as the MSS, the Korea Smart Factory Foundation (KOSF), and so on. While some institutions emphasize the technological foundation of Smart Factories like automation, on the other hand, others stress the organic and intelligent digital system itself.

Table 1. Various Definitions of Smart Factories

Classification	Definition
Ministry of SMEs and Startups (MSS)	(1) An intelligent factory that controls and improves production processes based on data and produces optimized products with the lowest cost and time. (2) A human-centered intelligent factory that produces customized products with the lowest cost and time by combining all production processes through ICT technology.
Korea Smart Factory Foundation (KOSF)	Intelligent flexible manufacturing factory which improves productivity, quality, and customer satisfaction by applying ICT technology in all processes of manufacturing.
Ministry of Science, ICT & Future Planning	Cyber-Physical system-based intelligent production place which acquires optimized solutions for responding to all outer environmental changes from machines of a factory.
Deloitte Korea	A factory that applied three functions (sensor, control, actuator) and operates each function organically like a human being.
LG CNS	A factory that has production competitiveness through optimized factory operation design and its manufacturing operation system based on industry/customer's traits, as well as supply of intelligent facilities.
CISCO Korea	A factory that advances intelligent production facility design, manufacturing environment, and control over facilities through ICT for asset utilization and supply chain and distribution innovation.

Source: Research Report of Ministry of SMEs and Startups. (2022.6).

Looking at the policies related to Smart Factories, the Ministry of Trade, Industry and Energy (MOTIE) announced the manufacturing 3.0 strategy in June 2014 and proposed the promotion of smart manufacturing. Due to the reorganization of the government in 2018, the MSS received the Smart Factory supply project from the MOTIE. The MSS and related ministries jointly announced the Smart Manufacturing Innovation Strategy for small and medium-sized enterprises in December 2018, and smart manufacturing innovation policies and projects are being promoted, such as 1) Supplying 30,000 Smart Factories, 2) Building 10 leading smart industrial complexes, 3) securing quality manufacturing jobs, etc. Table 2 shows these major policies and activities related to Smart Factories.

Table 2. Main Policies and Activities of Smart Manufacturing in Korea

Date	Main Contents
Jun. 2014	Establishment of 「Manufacturing Innovation 3.0 Strategy」
Jul. 2014	Establishment of 'Manufacturing Innovation Committee' for setting up following policies. - It is composed of 26 members from sector experts, economic organizations, and public officers and its main duty is diagnosing problems in Korean Manufacturing industry, collecting public opinion and discussing operation methods.
Mar. 2015	Announcement of implementation plan for 「Manufacturing Innovation 3.0 Strategy」
Jul. 2015	Establishment of Bureau of Smart Factory
Apr. 2017	Announcement of 「Smart Manufacturing innovation Vision 2025」 for leading the 4th industrial revolution
Mar. 2018	Announcement of 「Smart Factory Proliferation and Advancement Strategy」
Dec. 2018	(1) Announcement of 「Manufacturing Industry Vitality Recovery and Innovation Strategy - Composed with smartification of factory, industry cluster and design competency innovation, etc. (2) Joint ministries announcement of 「SMEs Smart Manufacturing Innovation Strategy」
Mar. 2019	Announcement of 「Smart Manufacturing Skills R&D Roadmap」 as follow up task of 「Manufacturing Industry Vitality Recovery and Innovation Strategy」
Jun. 2019	Joint ministries announcement of 「Vision and Strategy for Manufacturing Industry Renaissance」
Jul. 2019	Establishment of 'Bureau of Smart Production Innovation' as part of 「SMEs Smart Manufacturing Innovation Strategy」 - Overall management body of smart factory policies.
Nov. 2019	Establishment of 'AI·Manufacturing data Strategy Committee'
Jul. 2020	Announcement of 「AI·Data based SMEs Manufacturing Innovation Advancement Strategy」 - Setting up Blueprint of AI·Data-based SMEs Smart Manufacturing
Nov. 2020	(1)Announcement of 「Intelligent Manufacturing Innovation Implementation Strategy」 for alteration of policy focus from quantitative supply to qualitative advancement. (2)Establishment of 'Smart Manufacturing Innovation Association' as an private-driven platform for a proliferation of Smart Production

Source: Research Report of Ministry of SMEs and Startups. (2022.6).

Meanwhile, how is the level of Smart Factories defined? According to the MSS's report (2022) on Smart Factory, Smart Factory is defined as an intelligent factory that integrates product plan, design, production, distribution, and sale through Information and Communications Technology (ICT) and produces customer-fitted items at the lowest cost level. The report notes that the level of Smart Factory divides into 5 phases depending on the ICT utilization and competency. The lowest phase is the stage of unutilized ICT and it increases from level 1 to 5. In the level 1 phase, the Smart Factory can set up a standardized data system and collect and manage the data. And in the level 2 phase, the Smart Factory can conduct real-time data monitoring through the IoT devices installed in facilities, materials, and employees. In the level 3 phase, it means those data can be used for fast decision-making by real-time data analysis and in the level 4 phase, production can be optimized by an interlocking facility between an auto control system and factory administrating system. In the last level, customized flexible manufacturing can be conducted with the help of a self-decided, network-connected intelligent device.

As the MSS's report points out that most of the Smart Factories so far are at a low level, and only a few Smart Factories are at an advanced level with utilizing data and artificial intelligence (AI). As discussed by the MSS's report, almost 80% of the factory is level 1 to 2, level 3 factory which collects data in real-time is 18.6%, and level 4 factory which optimizes its production is only 1.4%. Overall, it can be said that government-driven Smart Factory supply ends up with just replacing part of the factory rather than improving the company's smart production innovation competency.

Chung S. et al. (2019) show the level of Smart Factory in two ways: (1) the Level of system integrity (how the production activity of the factory is organically integrated); and (2) the Level of data share and utilization (how much data that acquired from each production activity are collected, shared and utilized). Along with that, they insisted that the budget should be redistributed to consulting, education, and human resource development area rather than focus on the quantitative expansion of technical support.

2.2 Education and Training

The concept of education and training can be defined in many aspects. Nadler, L., & Nadler, Z. (1989), for example, suggest that education and training in industries are defined broadly so that can encompass the concept of education, training, and development; Education means learning something that employees do not perform, but they are expected to perform in near future. Training is conducted to improve the performance of employees' current work and development is defined as a study of someone's general achievement regardless of the relevance to their work. Hwang S. (2007) suggested that education and training enhance a worker's abilities such as general ability, technological ability, and problem-solving ability, and in the short term, which is assumed that task element does not change, skill cumulated through a worker's education, training, and experience.

Regarding the necessity and effectiveness of corporate education and training, Lucas (1988) suggest the endogenous growth theory that endogenic innovation through internally developed skill and knowledge can lead to sustainable economic development. Thus, investment in education and training can be perceived as a key factor for maintaining competitiveness and the driving force of value creation. Black & Lynch (1996) support that as a result of empirical analysis, it was shown that human capital is an important determinant of establishment productivity, and training impacts productivity at a certain point in time. A study conducted by Almeida, et al. (2012) shows that education and training not only improve laborers' competency and skills but also be the foundation of the long-term growth of the company.

Regarding the relationship between education and training and skill, Becker (1964), and Schultz (1961), among others, insist that investment in education and training for workers can be a factor in skill development. Accordingly, it is believed that investment in education and training for individual employees can be a factor in skill formation. The annual growth rate of education was also used as an indicator of the degree of skill of workers as shown by Thurow (1999).

However, despite these positive aspects of education and training, investment in education and training may be limited due to various obstacles. For instance, according to Acemoglu & Pischke (1999), a firm benefits from training only when the worker does not change jobs, and higher turnover makes this less likely. To prevent failure, companies can reduce training costs or make employees pay a certain amount of money (Becker, 1964). Also, companies can decide to hire skilled workers rather than invest in education and training in the aspect of labor cost reduction (Kang S., 2010).

2.3 Smart Factory and Investment in Education and Training

Most of the previous studies on Smart Factories focus on analyzing the current status and identifying industry trends as it has been only a few years since the concepts of Smart Factories, such as 'Current Status of Smart Factories', 'Strategies for Introducing Smart Factories', 'Outcomes of Smart Factory Introduction', and so on. There is no research on the direct relationship between Smart Factories and education and training. However, regarding a Smart Factory as an aspect of technology introduction, previous studies can be found.

Black & Lynch (2001), Bresnahan et al. (2002), among others, emphasize the importance of human capital investment that has a complementary relationship with technology by analyzing the impact of IT adoption in the 1980s and 1990s. Accordingly, it can be seen that an important factor in determining a company's performance is to have an organization-specific human capital that can effectively utilize the introduced technology rather than the technology itself. Similarly, Kim S., & Lee G. (2016) suggest that re-education of existing skilled workers and education and training programs for a new workforce are needed with the spread of Smart Factories.

Meanwhile, according to the Ministry of Employment and Labor's (MOEL) Corporate Vocational Training Status Survey Report (2021), 33.1% of respondents said that insufficiently skilled workers affect companies negatively in 2021 (5.4% very high + 27.7% high shift), and 41.2% said 'strengthening vocational training for workers as an effort to solve problems caused by lack of skills. Therefore, this study aims to (1) examine the characteristics of SMEs' education and training and Smart Factory levels through panel data; (2) empirically analyze the relationship between education and training investment and Smart Factory levels; and (3) derive implications based on the analysis results.

III. DATA AND METHOD

3.1 Data Collection

Data were collected and maintained by the KLI's Workplace Panel Survey (8th Wave, 2019). Since information on Smart Factories is included in the 2019 data as an additional questionnaire, only 2019 data was used. The response to the education and training variables is the value obtained from the HR manager, and the response to the Smart Factory variables is the value obtained from the production manager.

The collection process and sampling method of the 2019 data of the KLI's Workplace Panel Survey are as follows: In 2019, Smart Factory (ICT) data were surveyed for manufacturing businesses that responded that they had factories (processes) for manufacturing and production. The 2019 data survey began on July 14, 2020, and was conducted for about 7 months until January 29, 2021. To sum up, a total of 2,795 businesses were surveyed, with a response rate of 85.5%. Among the samples, 2,698 (96.53%) were private sector businesses and 97 (3.47%) were public sector businesses. Also, 1,158 businesses have maintained past data and panels, and 1,637 new panel businesses have been surveyed.

To analyze the relationship between education and training investment and Smart Factory level, in this study, a binomial logistic regression was conducted for small and medium-sized manufacturing companies with 30 or more and less than 300 employees. The independent variables were set at the education and training investment, and the dependent variable was set at the level of a Smart Factory. To refer to the appendix, the survey was conducted on manufacturing businesses based on the 10th Korean Standard Industry Classification, excluding industries other than manufacturing under the 10th Industrial Classification. Except for the cases showing missing values in the variables of this study, the size of the final sample used in this study was 468.

3.2 Analysis Method

The STATA 17 version was utilized for analysis. First, a correlation analysis was conducted to confirm the correlation between independent variables. Next, binomial logistic regression was conducted to confirm the determinants of the Smart Factory level. The binary logistic regression analysis model that analyzes the statistical probability between Smart Factory levels according to the characteristics of education and training investment is as follows:

$$\ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 CHARGE + \beta_2 PLAN + \beta_3 EDU + \beta_4 TIME + \beta_5 PART + \beta_6 COST + \beta_7 SIZE + \beta_8 SALE + \beta_9 YEAR$$

The dependent variables of the above model are the levels of Smart Factories, and the independent variables are existence of a person (department) in charge of education and training (*CHARGE*), education and training pre-planning (*PLAN*), important education and training contents (*EDU*), an annual average of training hours per person *(TIME*), the participation rate in education and training (*PART*), and education and training cost per person (*COST*), and control variables are a total number of employees (*SIZE*), sales (*SALE*), and the age of company (*YEAR*).

3.3 Variables and Definitions

3.3.1 Dependent Variable: Level of Smart Factory

In the KLI's Workplace Panel Survey, the level of smart production process is classified on a six-point scale. The lowest level (1 point) is the level of manually preparing a production plan, and the 2nd level (2 points) is the level of production management with Excel. The 3rd level (3 points) is production management using Management Information System (MIS), and the 4th level (4 points) is automatically problem detection and remote control through data. The 5th level (5 points) is an optimization of the entire process through big data such as comprehensive control, problem prevention, and optimization solutions. The highest level (6 points), is the level of autonomous problem identification and resolution without human support. In this study, referring to the definition of the Smart Factory level by the MSS, the level of 1 to 2 points of execution level of the smart production process were defined as the 'Basic level' of the Smart Factory, and the level of 3 to 5 points were defined as the 'Intermediate level' of the Smart Factory. The six-point level corresponds to the level of 'Smart Factory advancement', but since there are no businesses that have reached that level, it was ignored in this study.

Table 3 summarizes the frequency and average of the level of Smart Factory, which are the main variables of interest in this study. According to the frequency analysis results, 59.61% of businesses do not manage the work with information management systems, and only 40.38% of businesses can collect production information and track problems through information management systems. Looking at the average value of this variable, it can be seen that the level of Smart Factories of small and medium-sized manufacturing companies is quite low at about 2.3 points.

Table 3. Level of Smart Factory: Frequency and Average (N=468)

Classification		Variables	N	%
Dependent Variables	*Basic Level of Smart Factory=0*	[***Zero***] Manually writing down checklist or production journal	88	18.80
		[***Check***] Managing production journal or checklist on EXCEL and establishing simple plan	191	40.81
	Intermediate Level of Smart Factory=1	[***Monitoring***] Production records are systemically managed and production information can be checked and traced at any time	169	36.11
		[***Control***] Automatically sensing malfunction through data in real-time and solving problems through remote control	16	3.42
		[***Optimization***] Utilizing big data and optimization solutions, a factory can optimize the whole production process and conduct comprehensive control and prevent malfunction	4	0.85
	[***Autonomous operation***] Barely human intervention, materializing optimized factory which can autonomously control and solve the malfunction when it occurs		0	0
		Mean (Standard Deviations)	2.267 (0.832)	

3.3.2 Independent Variables: Investment in Education and Training

In this study, the independent variables, education and training investment variable, was defined by dividing it into education and training *plan* and education and training *operation* aspects. The education and training *plan* was defined as a variable for existence of a person (department) in charge, pre-planning establishment, and main training contents, and education and training *operation* was defined as an annual average of training hours per person, a ratio of training participation, training cost per person.

1. ***Existence of a person (department) in charge.*** Existence of a person (department) in charge. The existence of a person (department) in charge is one of the determinants that can enhance the performance of an investment in education and training as shown by Kang S. et al. (2002). In this study, the existence of a person (department) in charge of education and training made a dummy variable. The categorical variable '1=there is a department in charge of, 2=there is no dedicated department, but there is a person in charge of, and 3=nothing' re-coded as 1 (there is a person or department in charge of), and 0 (nothing).

2. ***Pre-planning establishment.*** Pre-planning establishment. About the questionnaire "Did you plan for the education and training for last year?", the categorical variable '1=Yes, 2=No' changed the dummy variable to 1 (pre-planning) and 0 (no pre-planning).

3. ***Main training contents.*** Main training contents. The more linked the content between job and education, the more positive the education and work performance have as discussed by Kwak N. et al. (2008). So, regarding the questionnaire "What is the important training content you conducted at your workplace last year?", it was answered in two categories; (1) IT-related education (general IT education, and professional IT education), and (2) Non-IT education (supervision education (leadership, decision-making), organizational development training (teamwork, problem-solving), office administration training, expert training, quality control training, sales training, industrial safety, and health training, labor relations education, foreign language education, liberal arts education, etc.). General IT education and

professional IT education variables were regarded as IT-related education and the value of each response was combined to create a sum variable; The sum variable value '1=general or professional IT education, 2=general and professional IT education was transformed into '1=IT education is important.' Also, 'other education except IT is important' was transformed into '0=other education is important.'

4. ***Annual average of training hours per person.*** Annual average of training hours per person. The value of the annual average of training hours per person variable is the total number of training hours of workers who have received education and training for a year divided by the total number of workers at the same period. It re-coded into 1 (less than 10 hours) and 2 (More than 10 hours).

5. ***Ratio of training participation***. Ratio of training participation. Excluding legal education and training, the total number of workers who received education and training at workplaces during last year was calculated by dividing the total number of workers into 1) managerial, 2) professional and technical, 3) office, 4) production and 5) service and sales positions.

6. ***Training cost per person.*** Training cost per person. Training costs per person were calculated by dividing the total education expenses, excluding expenses of legal education and training, by the total number of workers. Total education expenses refer to the total expenses spent on education and training at the workplace and include related expenses such as tuition fees, training instructors' wages, facilities and equipment expenses, maintenance expenses, etc.

3.3.3 Control Variable

The control variables used in this study are the total number of employees, sales, and age of the company. Table 4 shows the operational definitions of variables other than the Smart Factory level used in the study.

1. ***Total number of employees.*** The total number of employees is a factor that causes economies of scale to work on investment in education and training. The higher the number of workers, the lower the marginal cost of training, so companies with a large number of workers can easily implement additional training investments (Nho Y. & Kim M., 2015).

2. ***Sales***. Sales were also estimated to affect investment in education and training, so they were included in the control variable and calculated by taking a log in the variable value. Previous studies by Park S. & Oh M. (2007) showed that companies with larger assets or higher sales have higher training rates, and companies' investment in education and training expenses varies depending on the size of the workplace or total assets (Cho J. & Park S. 2007).

3. ***Age of company***. Based on previous studies by Park S. & Oh M. (2007) that the lower the age of the company, the higher the probability of conducting education and training, the age of the company was included in the control variable. It could be a difference in investment in education and training depending on the age of the company. The age of the company was calculated by subtracting the value of the company's establishment year from the survey year (2019) and re-coded as 1 (less than 7 years) and 2 (more than 7 years). It

was based on 7 years, which is the standard year for start-ups under the Support for Small and Medium Enterprise Establishment Act.

Table 4. Operational Definition of Variables (N=468)

Classification		Variables	Operational Definition		N	%
Independent Variables	*Education and training plan*	Existence of a person (department) in charge	Exist=1		445	95.09
			Not exist=0		23	4.91
		Pre-planning establishment	Established=1		81	17.31
			Unestablished=0		387	82.69
		Main training contents	Focus on IT education=1		76	16.24
			Focus on other education=0		392	83.76
	Education and training operation	Annual average of training hours per person	Combined training hours of training participants/total number of employees	Less than 10 hours=1	236	50.43
				More than 10 hours=2	232	49.57
		Ratio of training participation	(Total number of training participants/total number of employees)*100		468	100
		Training cost per person	Total training cost/ total number of employees		468	100

Control Variables	Total number of employee in 2019		[Small] Less than 50=1	87	18.59
			[Mid] 50~300 =2	247	52.78
			[Large] More than 300=3	134	28.63
	Sales	ln(sales of 2019)		468	100
	Age of company	Basic year (2019)-the year of establishment	Less than 7 years=1	10	2.14
			More than 7 years=2	458	97.86

Using the variables described above, I checked whether the characteristics of the education and training plan are factors that determine the level of the Smart Factory (Model I), and examined whether the characteristics of the education and training operation are factors that determine the level of the Smart Factory (Model II). Finally, the analysis was conducted by adding the characteristics of the education and training plan and the characteristics of the education and training operation (Model III).

IV. DATA ANALYSIS

4.1 Correlation Analysis between Independent Variables

The results of the correlation analysis between independent variables are shown in Table 5. The correlation between pre-planning establishment and the existence of a person (department) in charge is r.=-0.288 (p<.001). The correlation between pre-planning establishment and an annual average of training hours per person was found to be r.=-0.115 (p<.05). In addition, the correlation between the ratio of training participation and an annual average of training hours per person was found to be r.=0.137 (p<.01). The correlation between training cost per person and an annual average of training hours per person was r.=0.126 (p<.01), showing a significant positive correlation. The correlation between training cost per person and the ratio of training participation is r.=0.107(p<.05), showing a significant positive correlation.

Meanwhile, if the correlation coefficient between independent variables is 0.8 or more, there is a risk of multicollinearity. As a result of the analysis, the correlation coefficient between independent variables was less than 0.8, so it was analyzed that there was no variable to suspect multicollinearity.

Table 5. Correlation Analysis Result between Independent Variables

Classification	1	2	3	4	5	6
1. Existence of a person (department) in charge	1					
2. Pre-planning establishment	-0.288***	1				
3. Main training contents	-0.007	-0.048	1			
4. Annual average of training hour per person	-0.012	-0.115*	0.062	1		
5. Ratio of training participation	0.018	-0.076	-0.003	0.137**	1	
6. Training cost per person	0.004	-0.079	0.044	0.126**	0.107*	1

*Notes. * p<.10, ** p<.05, *** p<.01.*

4.2 Binary Logistic Regression Analysis for Smart Factory Level

The results of the analysis by inputting the characteristics of the education and training plan and the characteristics of the education and training operation to identify the factors affecting the level of the Smart Factory are shown in Table 6 below. [Model I] is a model using the characteristic variables of the education and training plan, and existence of a person (department) in charge, pre-planning establishment, and main training contents were input. The research model of [Model I] was found to be statistically significant (Chi-square=16.27, $p<.05$). Main training contents conducted (Coef.=-.810, $p<.01$) was found to have a significant relationship with the level of Smart Factories. In other words, it was analyzed that the more important education other than IT is conducted, the higher the level of Smart Factories. On the other hand, it was confirmed that the existence of a person (department) in charge and the pre-planning establishment were not significant determinants at the level of a Smart Factory.

Secondly, [Model II] is a model that utilizes variables such as annual average of training hours per person, ratio of training participation. As a result of the analysis, it was confirmed that the characteristics of education and training operation were not significant determinants of the level of Smart Factories.

Finally, [Model III] was found to be statistically significantly suitable as a model including both the variables of [Model I] and [Model II] (Chi-square=21.53, $p<.05$). When compared to [Model I] variable, significant variables were found to be significant as they were, and all of the [Model II] variables were also not significant.

Table 6. Binominal Logistic Regression Result about Level of Smart Factory

Variables	Dependent Variables (Level of Smart Factory)					
	Model I		Model II		Model III	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Existence of a person (department) in charge	0.290	0.493			0.331	0.497
Pre-planning establishment	-0.185	0.272			-0.175	0.276
Main training contents	-0.810**	0.284			-0.830**	0.285
Annual average of training hours per person			0.321	0.197	0.341	0.200
Ratio of training participation			-0.001	0.000	-0.001	0.000
Training cost per person			0.000	0.003	0.000	0.003
Total number of employees in 2019	0.119	0.200	0.090	0.198	0.094	0.202
Sales	0.087	0.070	0.072	0.070	0.083	0.071
Age of company	-1.034	0.664	-0.831	0.662	-0.987	0.668
Chi-square	16.27*		11.22		21.53*	
N			468			

*Notes. * p<.10, ** p<.05, *** p<.01.*

V. CONCLUSION

The purpose of this study was to confirm the influence relationship between the characteristics of the education and training plan and the characteristics of the education and training operation on the level of the Smart Factory. The analysis results of the study are as follows.

First, it was confirmed that the existence of a person (department) in charge was not a significant determinant of the level of Smart Factories. If the Smart Factory level is considered to be the result of education and training investment, these research results contrast with the results of research by Kang S. (2002). As analyzed by Kang S, it shows that not only the existence of a person (department) in charge, but also other factors play an important role. For example, in the study of Kang S., whether the training department (system) and the department (system) of human resources are combined or not is an important determinant of training investment to ensure that the results of education and training are reflected in promotion, wage, and so on.

Second, it showed that the pre-planning establishment for education and training was not a significant determinant of the level of Smart Factories. What is more important than this is the main training contents. It was analyzed that the more important education other than IT is conducted, the higher the level of Smart Factories. According to Kim J. (2017), the characteristic of Smart Factory-related education programs for manufacturing companies is that usually focused on operating software or hardware. For example, education about ERP systems, process simulation software, SPC (Statistical Process Control) software, big data, etc. is usually conducted. The problem is that the contents of the training do not fully consider the production site, resulting in a gap with the site. To sum up, education and training related to

Smart Factories for manufacturing companies are mainly supplied with IT education, but it should be considered that education other than IT can also be a significant determinant of the level of Smart Factories. Therefore, it is necessary to closely examine whether the contents of education and training are not separated from the field or whether it is educational contents that are helpful for the operation of Smart Factories.

Third, it was confirmed that the annual average of training hours per person, ratio of training participation, and training cost per person were not significant determinants of the level of Smart Factories. A general study found that education and training operation characteristics had a significant effect on productivity and corporate performance, but as in this study, these education and training operation characteristics were not significant determinants at the smart factory level. Cho S. & Lee Y. (2020) analyzed that the amount of companies' investment in training tend to increase and decrease rapidly over time and have low sustainability especially in the manufacturing industry compared to others. Thus, the characteristics of education and training operation are expected to be affected by the passage of time, so if these time effects are properly controlled, other research results may appear. In future studies, it is necessary to input more diverse variables, collect data more widely at time intervals, and analyze them.

In this study, the model was estimated by setting the dependent variable and the independent variables at the same time point. So, it should consider the problem of reverse causality. A more convincing study can be conducted by estimating the model by applying the time difference. In addition, quantitative measurement by the level of Smart Factory such as planning, design, manufacturing, process, distribution, and sales, as well as the level of smart in the production process, should be possible. To reflect these data in related policies will also be a task to be carried out in the future.

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APPENDIX

10th Korean Standard Industrial Classification: Manufacturing Industry

10. Manufacture of food products
11. Manufacture of beverages
12. Manufacture of tobacco products
13. Manufacture of textiles, except apparel
14. Manufacture of wearing apparel, clothing accessories and fur articles
15. Manufacture of leather, luggage and footwear
16. Manufacture of wood and of products of wood and cork; except furniture
17. Manufacture of pulp, paper and paper products
18. Printing and reproduction of recorded media
19. Manufacture of coke, briquettes and refined petroleum products
20. Manufacture of chemicals and chemical products; except pharmaceuticals and medicinal chemicals
21. Manufacture of pharmaceuticals, medicinal chemical and botanical products
22. Manufacture of rubber and plastics products
23. Manufacture of other non-metallic mineral products
24. Manufacture of basic metals
25. Manufacture of fabricated metal products, except machinery and furniture
26. Manufacture of electronic components, computer; visual, sounding and communication equipment
27. Manufacture of medical, precision and optical instruments, watches and clocks
28. Manufacture of electrical equipment
29. Manufacture of other machinery and equipment
30. Manufacture of motor vehicles, trailers and semitrailers
31. Manufacture of other transport equipment
32. Manufacture of furniture
33. Other manufacturing
34. Maintenance and repair services of industrial machinery and equipment