# ANALYSIS TOOL FOR SMART FACTORY TECHNOLOGY CAPABILITY OF MANUFACTURING FIELDS

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## Abstract

Manufacturing industry has established its smart technology environment appropriate for its manufacturing fields in order to increase its manufacturing competitiveness. The smart technology capability of manufacturing fields is very critical for the innovative production and operation activities, and for efficient improvement of the manufacturing performance. A reasonable analysis framework needs to efficiently analyse smart technology ability of manufacturing fields in order to effectively manage and improve its smart technology capability. This research verified the developed analysis scale for smart factory technology capability of manufacturing fields by reliability analysis and factor analysis based on previous literature. This study presents a 12-item analysis tool that can gauge the smart factory technology capability of manufacturing fields.

**Keywords:** smart technology, smart factory, smart technology capability, analysis item, analysis tool

## Introduction

The rapid development of information technology (IT) has affected whole areas of industries. Especially in manufacturing industry, it helps enterprises deal with various requirements of customers and frequent variations of manufacturing environment (Jung et al., 2013). World experts present that the fourth industrial revolution brings big changes and growth in manufacturing fields (Accenture, 2016; Wold Economic Forum, 2016; Baur and Wee, 2015). Globalization, unpredictable markets, increased products customization and frequent changes in products, production technologies and machining systems have become a complexity in today's manufacturing environment (Park and Tran, 2015). Manufacturing industry of the future will be characterized by the smart factory, smart product, and smart service (Kagermann et al., 2014).

Manufacturing fields has utilized diverse IT for efficient production activities and innovative operation performance in manufacturing fields. Manufacturing areas also have built smart technology environment to increase its production activities and productive performance, and to increase its industrial competitiveness in a global industry environment. It is applying smart technology to the production plan, production activities, production management, and product service activities to improve their manufacturing activity performance. Smart technology is a crucial mediator to control and increase the manufacturing productivity in continuous changing industry environment. In this manufacturing environment, smart technology is an important resource for future advanced manufacturing environment. It is indispensable for widely applying smart technology to all manufacturing activities. We have to systematically build smart technology environment to manage and improve reasonable manufacturing capability appropriate for its manufacturing activity and performance. That is, we have to analyse its smart technology capability with a scientific and practical analysis scale in order to effectively build and advance a smart technology environment appropriate for the manufacturing fields. The analysis framework of objective criteria should improve smart technology capability of manufacturing areas based on the analysis results of smart technology ability for manufacturing fields. But previous studies have not researched a reasonable tool to analyse a smart technology capability of manufacturing fields. We need an objective framework that can efficiently analyse a smart technology capability of manufacturing fields. In this research, we present a practical framework that can reasonably analyse the smart technology capability for a smart factory of manufacturing fields.

Hence, this study develops a structural tool that can efficiently analyse a smart factory technology capability (SFTC) to effectively perform manufacturing activities and to systematically improve its smart technology capability in terms of a smart technology appropriate for a smart factory.

## Previous research

New technologies and methods are researched for the next stage of manufacturing fields (Park and Tran, 2015). Numerous researches in manufacturing fields to achieve an intelligent manufacturing have been reported in the literature (Park and Tran, 2015). The research area can be presented as follows: Technologies for the advanced information systems such as networked process planning, industrial network, inheritance of data, and information and communication technology (ICT) for industry (Park and Tran, 2015): Evolvable hardware/software such as integration of industrial systems, intelligent diagnosis, effective maintenance for equipment and system, hi-tech machinery industry and intelligent sensors (Park and Tran, 2015); Innovative systems for intelligent manufacturing to flexibly and quickly adapt to new challenges of manufacturing environment (Park and Tran, 2015).

In smart technology of manufacturing industry, smart factory includes smart products (smart service), smart data (big data and machine learning), and smart operation (human-technology-integration) in trustworthy cloud infrastructures (Lee, Kim, and Lee, 2017). It can be explained as an extended version of process innovation to continuously improve the existed process based on collection of data and control of process in real time (Lee, Kim, and Lee, 2017). Korea Ministry of Trade, Industry and Energy presented the 18-detailed technologies of 4 domains (application, platform, device and network, and interactive operability and security) as smart factory technology development roadmap (Korea Ministry of Trade, Industry, and Energy, 2015). Application technology generally includes human-centred work support technology, smart factory integration operation and service technology, and smart retailing and procurement logistics technology (Korea Ministry of Trade, Industry, and Energy, 2015). Platform technology indicates big data analysis, cloud systems, cyber physical systems, factory resource modelling and simulation, and production process control technology (Korea Ministry of Trade, Industry, and Energy, 2015). Device and network technology presents cognitive smart sensor technology, industrial gateway technology, and smart factory network technology (Korea Ministry of Trade, Industry, and Energy, 2015). Interactive operability and security technology refers to smart factory standardization technology, software reliability and security, and data protection and remote control technology (Korea Ministry of Trade, Industry, and Energy, 2015).

In smart technology environment, manufacturing firms are satisfying the diverse needs of customers through reducing product cost, high quality of manufactured goods, and shortening period of delivery and development of products with IT solutions for firms such as ERP (Enterprise Resource Planning), SCM (Supply Chain Management), and PLM (Product Lifecycle Management) (Lee, 2003). Furthermore, through complete fusion of manufacturing industry and ICT, the existing factories will be changed into perfect smart factories in which not only automated production but also control and maintenance of overall processes and safety management are possible (Lee and Kim, 2014; Kim et. al, 2014).

Smart manufacturing system is a manufacturing system to produce high value products and to build a smart factory, based on various ICT technologies for real-time monitoring, sensor networking, and facility condition diagnosis and equipment operation (Jang and Kim, 2016). To establish a smart manufacturing factory, the equipment in a manufacturing factory is required to be connected with various elements and services in and out of the factory (Lee, Lee, and Song, 2015). Smart factory technology is classified by ICT as industrial control systems, MES, ERP, PLM and field device technology as industrial network, RFID systems, industrial robot, and control devices (Cho and Lee, 2014).

In previous literature of smart factory solutions, researches have presented solution departments of smart factory as factory field automation, factory operation and optimization in real time, production and process development, optimization of supply chain management, and enterprise resource management (Fedorov et. al, 2015; Gourgand and Kellent, 1992; Kang, Park, and Youm, 2017; Xu and Hua, 2017). Finally, the smart technology for smart factory in manufacturing industry can be explained as smart technology related to smart production, smart data, and smart operation in terms of the efficiency of product production, efficient demand response, and satisfaction of customer service.

With exploring previous literature and our research results, this research defines the smart factory technology capability (SFTC) as the total smart technology capability that a factory has to retain to efficiently support for smart production, smart data, and smart operation in terms of a smart technology of manufacturing fields. We develop the first analysis items for SFTC based on the definition of SFTC and previous studies related to smart technology of smart factory.

## Methods

### 1. Research method

At first, this study developed an initial list of 22 analysis items for SFTC based on definitions and components of smart factory technology capability (Park and Tran, 2015; Kagermann et al, 2014; Lee, Kim, and Lee, 2017; Korea Ministry of Trade, Industry, and Energy, 2015; Lee, 2003; Lee and Kim, 2014; Kim et. al, 2014; Jang and Kim, 2016; Lee, Lee, and Song, 2015; Cho and Lee, 2014; Fedorov et. al, 2015; Gourgand and Kellent, 1992; Kang, Park, and Youm, 2017; Xu and Hua, 2017). We analysed the construct validity of the developed analysis items to ensure that the analysis items efficiently examine SFTC. This research verified that the analysis framework had a suitable operational definition of the construct. In order to confirm reasonable construct of the analysis tool for SFTC, we utilize a verification method presented in previous literature. Many studies presented various methods to verify the validation of a model construct (Etezadi-Amodi and Farhoomand, 1996; Torkzadeh and Doll, 1999; Torkzadeh and Lee, 2003; Mchancy, Hightower, and Pearson, 2002; Yoon, 2007).

Generally, most studies present two methods to verify a model construct validation: correlations between total scores and item scores, and factor analysis (Etezadi-Amodi and Farhoomand, 1996; Torkzadeh and Doll, 1999; Torkzadeh and Lee, 2003; Mchancy, Hightower, and Pearson, 2002; Yoon, 2007). The former assumes that the total score is valid, and the extent to which the item correlates positively with the total score is indicative of the construct's validity for the items (Etezadi-Amodi and Farhoomand, 1996; Mchancy, Hightower, and Pearson, 2002). Each item score was subtracted from the total score to exclude spurious part-whole correlation (Etezadi-Amodi and Farhoomand, 1996; Mchancy, Hightower, and Pearson, 2002): the result was a corrected item- total correlation that was then correlated with the item score. Factor analysis analyses the underlying structure or components of the framework (Torkzadeh and Doll, 1999; Torkzadeh and Lee, 2003). It helped identify factorally pure items that would facilitate more specific hypothesis tests, and to identify the components that make up the total measure (Torkzadeh and Doll, 1999; Torkzadeh and Lee, 2003; Yoon, 2007). The factor-analysed items were selected, since they were closely related to each other.

This research also confirmed an analysis scale of criterion-related validity to identify analysis items that may not be closely concerned with SFTC. The generalized item for efficiently analysing SFTC was used as a criterion analysis scale. The scale presented an analysis scale of criterion-related validity to the extent that each analysis item was correlated with this. Analysis items should present a favourable or unfavourable attitude toward the object in question (Mchancy, Hightower, and Pearson, 2002). When the analysis item is ambiguous or shows a neutral attitude, we should delete it (Mchancy, Hightower, and Pearson, 2002). We examined an analysis scale of criterion-related validity to identify analysis items that did not show favourable or unfavourable attitudes. This research took out all of the analysis items in an analysis scale from the domain of a single construct, and responses to these indicator items should be highly inter-correlated. The corrected item-total correlation refers to an analysis scale of this.

In this questionnaire survey, the analysis questionnaire used a five-point Likert-type scale as presented in previous studies; denoting, 1: not at all; 2: a little; 3: moderate; 4: good; and 5: very good. We carried out our analysis questionnaire for various firms in manufacturing fields. The questionnaire consists of three main sections. The first section represents the backgrounds and objectives, the main contents, and response methods of this questionnaire. The second section asks respondents to provide general information, such as manufacturing departments and position, firm's size and revenue, and business history of their firms. The last section presents the analysis items for the respondents in manufacturing fields. This research collected questionnaire data from a variety of manufacturing fields so that the analysis results can be generalized. We used two kinds of survey methods: direct collection and e-mail. The respondents either directly mailed back the completed questionnaires or research assistants collected them three-four weeks later. The collected questionnaires indicated 37.1 percent of all the target respondents.

### 2. Sample characteristics

In this questionnaire survey, we collected 128 responses form 345 respondents in four manufacturing fields. The responses indicated a variety of manufacturing fields and position, firm size and revenue, and business history. Our research ruled out four incomplete or ambiguous questionnaires, leaving 124 usable questionnaires for statistical analysis. The respondents in terms of manufacturing departments were classified as electrical and electronics (25.8%), machine (18.5%), chemistry (22.6%), and food and beverage (33.1%). The positions of respondents were identified as top manager (8.9%), middle manager (38.7%), and worker (52.4%). The respondents in four manufacturing areas had on average 8.8 years' experience (S.D. =1.13) in their manufacturing fields, their average age was 38.4 years old (S.D.=5.81), and their gender, male (71.8%) and female (28.2%). We executed our questionnaire survey focused on various manufacturing fields, and respondents with ample experience within manufacturing departments. That is, it is to obtain the reasonable and objective analysis results from this questionnaire survey.

### 3. Analysis and discussion

Our research extracted the analysis results from the collected questionnaires. The analysis items were excluded when their correlation with the corrected item-total correlation was < 0.5 or when their correlation with the criterion scales was < 0.6 (Etezadi-Amodi and Farhoomand, 1996; Mchancy, Hightower, and Pearson, 2002). The correlations with the corrected item-total correlation and the criterion item were significant at p ⍰ 0.01 and similar to those used by others in previous research (Torkzadeh and Doll, 1999; Torkzadeh and Lee, 2003; Yoon, 2007). We used factor analysis to verify the validity of the developed analysis framework and analysis items.

This study also performed factor analysis to identify the underlying factors or components that comprise the SFTC construct. This research excluded inadequate items for the analysis tool based on the factor analysis results. We considered sufficiently high criteria to extract reasonable analysis items of SFTC. Hence, the first 22 analysis items resulted in a 16-item scale prior to conducting factor analysis. The sample of 124 responses was investigated by using principal components analysis as the extraction technique with the varimax method of rotation. The analysis items with many multiple loadings may be good analysis items of SFTC, but this blurs the distinction between factors by including these items in the scale (Torkzadeh and Lee, 2003). The analysis items, having factor loadings greater than 0.3 on other factors, were excluded from the analysis tool to improve the distinction between factors (Torkzadeh and Lee, 2003).

*Table 1: Reliability, validity, and factor loading of SFTC construct*

| Variable | Factor Loading | | | Corrected Item-Total Correlation | Coefficients Alpha |
|---|---|---|---|---|---|
| | Factor 1 | Factor 2 | Factor 3 | | |
| V01 | 0.772 | | | 0.711 | |
| V03 | 0.789 | | | 0.697 | 0.802 |
| V04 | 0.678 | | | 0.682 | |
| V07 | 0.614 | | | 0.691 | |
| V08 | | 0.803 | | 0.743 | |
| V10 | | 0.815 | | 0.664 | 0.824 |
| V11 | | 0.763 | | 0.698 | |
| V13 | | 0.714 | | 0.687 | |
| V15 | | | 0.799 | 0.761 | |
| V17 | | | 0.813 | 0.673 | 0.798 |
| V19 | | | 0.717 | 0.639 | |
| V20 | | | 0.612 | 0.602 | |

* Significant at p □ 0.01

In addition, this research deleted four analysis items, since they had the lowest correlations with a criterion and the lowest factor loadings. These deletions resulted in a 12-item scale to analyse SFTC. One factor with Eigen value = 8.3 explained as explaining 68% of the variance. Each of the 12 analysis items had a factor loading > 0.600. As presented in Table 1, each of the 12-analysis items had a corrected item-total correlation > 0.600. The correlation for each of the 12 indicator items was positive and significant (p □□0.01). This 12-item tool had reliability (Cronbach's alpha) of > 0.790. Hence, the 12 analysis items present a reliable and valid analysis framework to analyse SFTC. However, we should endeavour to look for additional evidence of the analysis tool's validity and reliability, internal consistency, and more scientific and practical analysis items. Through reflecting the analysis results of many findings and case studies, the developed analysis tool can be became more objective and practical scale for the application of SFTC of manufacturing fields.

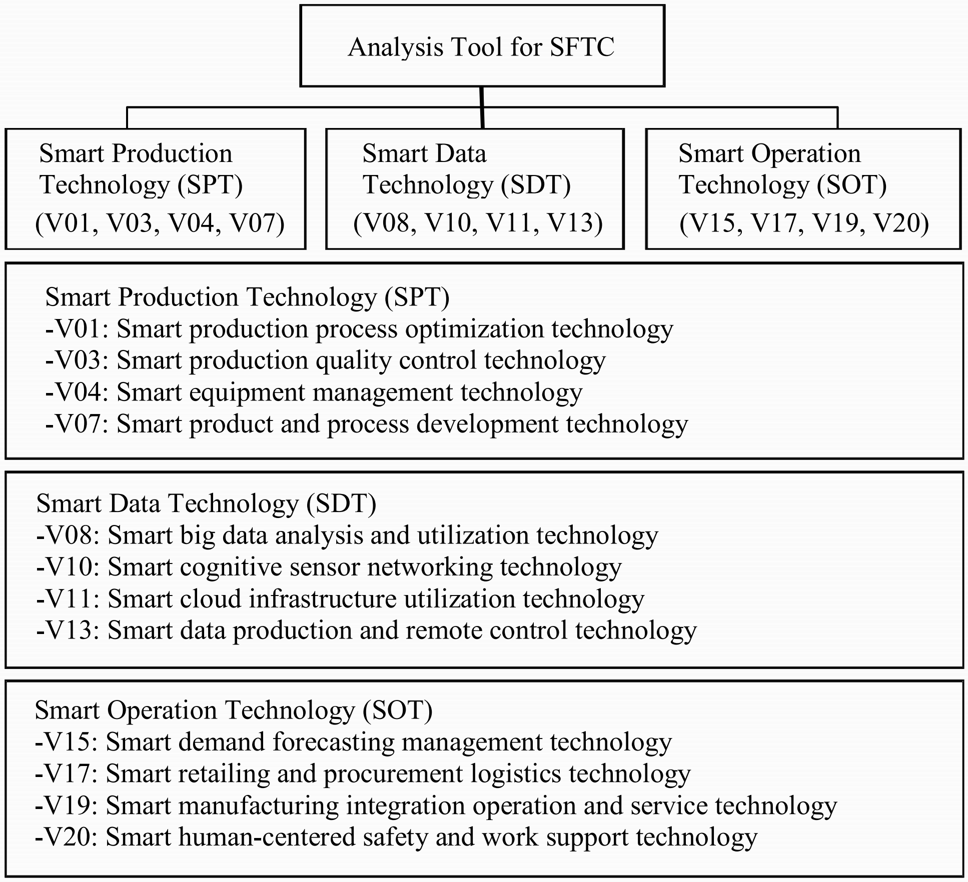
## Framework of analysis tool

This study developed the 12 analysis items appropriate for analysing SFTC. We identified three factor groups from our factor analysis results. The factor groups present the potential factors as major components to analyse SFTC. Through examining the analysis items of each factor group based on previous studies, this study identified the following three potential factors:

Factor 1: smart production technology; factor 2: smart data technology; and factor 3: smart operation technology. The extracted factors comprise the overall smart technology analysis content for SFTC. Smart production technology presents the smart technology related to product production and process management for smart factory. It includes production process optimization technology, production quality control technology, equipment management technology, and product and process development technology. Smart data technology indicates the smart technology related to analysis and utilization of big data and cloud infrastructure for smart factory. It has big data analysis and utilization technology, manufacturing resource modelling and simulation technology, cloud system utilization technology, and data production and remote control technology. Smart operation technology refers to the smart technology including demand forecasting, logistics, integration operation and service, and safety and work to support for smart factory. It comprises demand forecasting management technology, retailing and procurement logistics technology, manufacturing integration operation and service technology, and human-centred safety and work support technology. Finally, they explain a structural tool to analyse SFTC, including 3 analysis factors and 12 analysis items.

Hence, the developed tool consists of three analysis factors such as smart production technology, smart data technology, and smart operation technology as shown in Fig. 1. Each factor has four analysis items. As presented in Table 1 and Fig. 1, smart production technology has the analysis items such as V01, V03, V04, and V07. Smart data technology includes V08, V10, V11, and V13. Smart operation technology comprises V15, V17, V19, and V20. These analysis factors influence SFTC that means the comprehensive smart technology capability of smart factory. It is crucial to manage and improve SFTC by analysing smart factory technology ability with using a valid and reliable analysis framework. These findings can facilitate efficient advance of a smart technology capability for smart factory with reflecting the analysis results by applying the developed analysis tool to manufacturing fields. Analysing SFTC is an efficient method to understand the real situation for the SFTC of manufacturing fields. Therefore, understanding the SFTC structure is essential to analyse the success of SFTC that denotes the SFTC to efficiently support for manufacturing activities. This research results can utilize the structural tool to analyse SFTC for a smart factory of manufacturing fields.

*Figure 1: Framework of the developed analysis tool for SFTC*




In order to understand the mutual influence between analysis factors, this research presented the relation between the analysis factors, and the relation between each factor and SFTC. Since there are the factors affecting SFTC, understanding their mutual relation is very critical for efficiently improve SFTC and for the effective utilization of the developed tool in manufacturing fields. Their mutual relation is complex and may be affected by other variables. We analysed how they were correlated in order to examine the relation between smart production technology, smart data technology and smart operation technology, and SFTC, as showed in Table 2.

*Table 2: Correlation matrix*

| | | (2) | (3) | (4) |
|---|---|---|---|---|
| SFTC | (1) | 0.48 | 0.41 | 0.46 |
| Smart Production Technology | (2) | | 0.40 | 0.45 |
| Smart Data Technology | (3) | | | 0.43 |
| Smart Operation Technology | (4) | | | |

## Conclusion

This study provides a comprehensive framework that can analyse perceived SFTC of manufacturing fields. Perceived SFTC presents a smart factory technology capability in terms of a smart technology for manufacturing fields. The developed analysis tool with adequate validity and reliability provides a reasonable method for grasping the real situations for SFTC of manufacturing fields.

Therefore, this study provides a structural tool that can efficiently analyse the SFTC to manage and improve smart factory of manufacturing fields in terms of smart technology. Our findings provide a new direction and foundation for the development and advancement of the efficient analysis framework for SFTC. In future research, we will find the practicality and availability of this analysis tool by presenting the analysis results by applying it to many case studies.

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