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RESEARCH ARTICLE

Production System Maturity Model (PSMM) for Assessing Manufacturing Execution System

DAE-JUNG AHN, CHANGDONG JUN, SEUNGHWAN SONG, AND JUN-GEOL BAEK
Department of Industrial and Management Engineering, Korea University, Seoul 02841, South Korea

Corresponding author: Jun-Geol Baek (jungeol@korea.ac.kr)

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ABSTRACT In conjunction with Industry 4.0, the manufacturing execution system (MES) has emerged as an essential component for implementing smart factories. The complexity of product specifications and the need to manage production facilities more efficiently has generated a growing demand for digital transformation within MES and enhancement of MES to replace manufacturing operators or support engineers. However, the lack of concrete methods to assess the current utilization of MES poses challenges in efficiently addressing unmanned automation and digital transformation requirements. This study proposes a maturity model (MM) and corresponding index to measure the level of MES within companies. The model quantifies the degree of automation in manufacturing operations and production management processes. Expanding on the existing MM, this method proposes two dimensions (operation and management) to evaluate the MES maturity and balance index across 17 standard system modules. The proposed method aims to provide a tool for companies to prepare for advanced smart factories in the future. Using the proposed production system MM, we conducted a diagnostic assessment of the MES levels of 93 manufacturers, for the first time confirming the maturity index gap and balance index change patterns between operation and management systems across industry groups and revenue scales.

INDEX TERMS Production system maturity model, production system maturity index, production system balance index, manufacturing digital transformation, automated manufacturing execution.

I. INTRODUCTION

The digital age is characterized by rapid development, growth, and innovation, necessitating businesses to respond to change and anticipate and foster innovation [1], [2]. Digital transformation (DT) has emerged as a significant research topic concerning businesses [3], [4]. It involves leveraging information, computing, communication, and connectivity technologies to induce substantial changes in business attributes with the objective of enhancing performance [5]. Extensive literature reviews have been conducted on DT, reflecting the increasing attention focused on it [6], [7], [5]. Particularly, within the manufacturing industry, the development and implementation of DT have become crucial concerns for organizations. Monitoring and analyzing process-related data regarding production and product quality can yield positive effects on productivity and quality enhancement [8]. Therefore, an increasing number of manufacturing companies must augment their DT capabilities to secure a competitive advantage.

Although DT holds the potential for enhancing business processes and improving flexibility in manufacturing and logistics networks, the range of methods available to develop such strategies remains severely limited [9], [10]. The following processes need to be performed for manufacturing companies to successfully promote manufacturing DT that improves productivity and quality. Firstly, establishing a standardized system for collecting diverse data generated throughout the manufacturing process, encompassing equipment, processes, logistics, and the environment, utilizing technologies like the Internet of Things (IoT), programmable logic controller (PLC), and computer integrated manufacturing (CIM).

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Secondly, implementing factory automation systems to connect and utilize the data collected from facilities, facilitating control and operation based on the acquired data. Lastly, constructing a system to store, analyze, and optimize the collected data, integrating it into the factory automation system. To achieve this, specific and systematic diagnostic tools for each domain of the current manufacturing execution system (MES) are needed [11]. These diagnostic tools enable manufacturing companies to accurately assess their current level and establish smart factory development goals while specifying the required resources and directions for their activities [12].

The evaluation of DT often involves discussions on performance measurement, as evidenced in practitioner research. Various frameworks at the national and company-wide levels have been proposed for this purpose [13]. National frameworks aim to assess the level of DT within a specific country to inform policy decisions [14]. Conversely, company-wide frameworks focus on evaluating a company's DT position. Most DT maturity models measure DT capabilities across the organisation and provide conceptual guidance for defining objectives and necessary skills. However, their application in measuring the maturity of MES in real manufacturing companies or using them as frameworks to enhance manufacturing DT has limitations. Therefore, a comprehensive understanding of the role of manufacturing integrated databases in effectively supporting manufacturing DT has to be obtained. To achieve this, a highly practical maturity measurement model is required to identify the data that should be collected and provided by manufacturing operation systems [15]. Furthermore, it should outline how production management systems leverage this data to enhance valuable manufacturing DT capabilities.

This study presents a production system maturity model (PSMM) for evaluating the maturity of MES. Through the utilization of PSMM, manufacturing companies can evaluate and comprehend the current state of their MES. Additionally, they can establish development targets and goal levels by comparing their system average with other companies within the same or different industries. Hence, manufacturing companies can autonomously define smart factory implementation objectives that align with their specific processes and technological challenges. PSMM assesses maturity indices in five stages for each of the system modules that support manufacturing operations. Each maturity index is represented as a two-dimensional measure, encompassing the axes of operation and management, extending the one-dimensional maturity index. This enables manufacturing companies to evaluate the level of MES implementation in a module-by-module specific manner and formulate precise development roadmaps for each stage.

In this section, we provide a Table 1 with the full meaning of all abbreviations utilized within the paper. The rest of this study is structured as follows: Section II reviews existing maturity models in the DT domain. Section III introduces PSMM, the proposed approach. Section IV discusses the results and implications of the MES maturity survey experiment using PSMM. Section V highlights the significance study, limitations, and future research directions of this study, concluding the overall findings.

TABLE 1. List of abbreviations.

Abbreviation	Descriptions
ANOVA	Analysis of variance
APC	Advanced process control
APS	Advanced planning and scheduling
BI	Balance index
CIM	Computer integrated manufacturing
DT	Digital transformation
EI	Engineering intelligence
EPT	Equipment performance tracking
FDC	Fault detection and classification
IG	Industry group
IoT	Internet of Things
LC	Level classifier
MC	Machine control
MCS	Material control system
MDW	Manufacturing data warehouse
MES	Manufacturing execution system
MESA	Manufacturing Enterprise Solutions Association
MI	Maturity index
MIS	Management information systems
MM	Maturity model
MOS	Manufacturing operation system
OI	Operation intelligence
PLC	Programmable logic controller
PoP	Point of production
PSBI	Production system balance index
PSMI	Production system maturity index
PSMM	Production system maturity model
QMS	Quality management system
RG	Revenue group
RME	Reliability and maintenance engineering
RMS	Recipe management system
ROC	Remote operation control
SM	Smart manufacturing
SPC	Statistical process control
TC	Tool control
VM	Virtual metrology
WCS	Warehouse control system

II. RELATED WORKS

Maturity generally refers to a specific progression in the development of a system towards reaching a target state [16]. It can be considered a gradual process consisting of several sequentially ordered phases, each of which specifies requirements for that level of complexity. A comprehensive survey of maturity models (MMs) was conducted using research platforms such as Web of Science, Scopus, and Google Scholar. The survey covered a 10-year period from 2013. Keywords used in this literature review included 'Digital Transformation', 'Digitalization', 'Industry 4.0', 'Industry Internet of

Things', 'Production System', 'Maturity Model', 'Capability Model', 'Assessment Model', and 'MES Level' [17]. MMs enable objective assessment and impact analysis. It can also assess an organization's strengths and weaknesses or compare them to other organizations [18].

In this study, we employed the three MM evaluation criteria from previous research [19]. Additionally, we extended the PSMM criteria by incorporating seven additional necessary criteria for evaluating and enhancing a company's MES for continuous self-development. These supplementary evaluation criteria were chosen to address gaps identified in existing MMs and may require further refinement (For more information on how we evaluated the 25 MMs against the ten criteria, see Appendices A and B):

- *C1: MM should be published as an academic paper as an indicator of an academic approach*
- *C2: MM should include descriptions of components for providing detailed analysis*
- *C3: MM should be universal and not be limited to a specific industry domain in the manufacturing field*
- *C4: MM should establish a standardized definition of MES that applies to the entire manufacturing domain, along with a comprehensive maturity assessment method*
- *C5: MM should provide a detailed maturity assessment method at the MES module level*
- *C6: MM should establish a connection between manufacturing operation methods and MES maturity*
- *C7: MM should establish a connection between MES maturity and digital transformation using manufacturing data*
- *C8: MM should provide a self-assessment tool for companies to measure their maturity independently*
- *C9: MM should enable the comparison and benchmarking of system maturity levels across diverse manufacturing industries*
- *C10: MM should enable the evaluation of MES maturity based on a company's manufacturing domain and revenue scale*

Based on the survey results, 25 relevant research cases for developing DT and MM in smart manufacturing were identified. However, none of the existing MMs meet all the specified evaluation criteria. For instance, MM03, MM04, MM05, MM07, MM10, MM18, MM19, MM20, and MM21, published as white papers, fail to meet criterion C1. MM08, MM11, and MM14 offer preliminary MMs for specific components but lack defined maturity levels and detailed measurement attributes, thus not meeting the criterion C2. MM09 targets the telecommunications sector, MM12 focuses on the supply chain sector, and MM13 is designed for the Industry 4.0 strategy, thus not meeting criterion C3 [17].

A comparative analysis reveals that recently published MMs support some or all of the standardized MES definitions for the entire manufacturing domain. MM15, MM21, MM22, MM23, and MM24, among others, provide detailed maturity assessment methods. However, most MMs do not satisfy C8, which provides metrics for organizations to independently measure maturity, nor do they provide consideration of an organization's manufacturing domain and revenue size as required by C10.

This comparative study underscores the need for a holistic and integrated approach that considers all value-creation processes to fully leverage the benefits of DT. However, existing MMs lack this comprehensive and integrated approach. Most MM research does not aim to enhance the DT process and lacks detailed measurements for maturity. Additionally, none of these methods provides information on the specific modules of the MES or development levels that enable module-based maturity improvement. Furthermore, few cases offer detailed information on application models or action plans for enhancing maturity levels. Previous MMs also do not assess maturity in two dimensions. However, a two-dimensional assessment is necessary to identify differences in maturity and balance by industry and revenue size, as well as patterns of development, in order to help companies become more competitive.

Appendix B presents our evaluation of existing MMs against the PSMM criteria. The results show that while some models meet certain criteria, none comprehensively fulfil all the requirements. This underscores the need for a new MM that addresses all identified gaps. Consequently, our study aims to develop an MM that meets all the evaluation criteria, specifically for MES-based DT. The research methodology is detailed in the following section.

III. DEVELOPMENT OF PSMM

A. SELECTION OF PRODUCTION SYSTEM REFERENCE MODEL

A reference model is essential for assessing the maturity of a production system. One notable MES architecture model is the 'Strategic Initiatives Model' (Version #2.1, 2008) proposed by the Manufacturing Enterprise Solutions Association (MESA). In 1996, MESA introduced the fundamental 'MESA-11' model, which defined MES based on 11 core functions. Later, in 2004, the original model from 1996 was expanded to encompass business operations, supply chain optimization, and asset optimization, known as 'C-MES' [20].

The 'MESA-11' model primarily focuses on automating process and equipment operations through Core Functions. In contrast, 'C-MES' expands the functional scope to include supply chain and asset domains by incorporating the enterprise business operations domain and illustrating their interrelationships. In 2008, MESA introduced the 'Strategic Initiatives Model', as shown in Figure 1, which builds on the core functions of the 'MESA-11' model and organizes MES functions into ten categories at the manufacturing/production operations layer. It incorporates business operations from 'C-MES' at the layer above and strategic operation functions as strategic initiatives to depict their interrelationships (For detailed descriptions of specific features, see the Supplementary Material A).

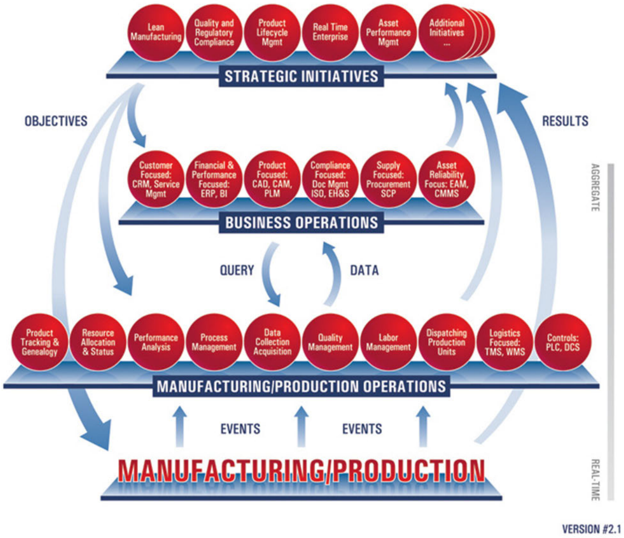


FIGURE 1. Strategic initiatives model, MESA 2008.

The 'MESA-11' model highlights how events and data flow from the manufacturing/production operations layer to the business operations layer, which then informs strategic initiatives. Conversely, the strategic objectives and results drive the business operations and, ultimately, the manufacturing/production activities, ensuring a cohesive and integrated approach to manufacturing management.

Since the release of MESA's 2008 model, which significantly influenced the architecture composition of existing MES for manufacturers, fourteen years have passed. Thus, in this study, we have selected the MESA model as a suitable reference model for evaluating the maturity of real-world production systems. The 'Smart Manufacturing' Model developed by MESA in 2022 has not yet been released, and as there are no actual application cases, it has been excluded from this study.

B. NECESSITY OF PSMM AND DEFINITION OF MEASUREMENT TARGETS

1) NECESSITY OF PSMM

Manufacturing companies worldwide are increasingly expanding their production plants and actively pursuing the development of smart factories to enhance productivity and quality. However, the absence of systematic tools and guidelines to accurately assess the operational level of MES and establish specific developmental stages and goals has resulted in delays in decision-making for advanced investments in manufacturing systems. This delay, in turn, hampers the timely achievement of desired outcomes.

Existing DT maturity models have proven challenging when assessing the maturity level of manufacturing companies' production systems. Although abstract concepts and overall functional descriptions for smart factories are available, specific criteria and indicators for diagnosing the presence of actual system modules and their maturity levels at each stage within MES are lacking. To address this gap, we redefined the standardisation target for level diagnosis by integrating MES modules used in real-world manufacturing sites based on the MES reference functions defined by MESA. Consequently, we developed a PSMM to diagnose their maturity. In addition, we introduced the production system maturity index (PSMI) and production system balance index (PSBI) as objective measures to index the results of the level diagnosis, thereby quantifying the current level of a company's smart factory.

2) DEFINITION OF REFERENCE ARCHITECTURE FOR MES

Diagnosing and indexing the level of an MES using MESA's unmodified logical model presents diagnosis challenges due to its lack of direct mapping to real-world MES implementations in manufacturing plants. MESA's model categorizes the manufacturing system into strategy, business, and manufacturing, assigning specific functions to each domain.

In this study, we addressed a limitation of the logical model by incorporating the physical systems necessary for executing. Although this logical model provides an accurate definition of functions, it does not mention the physical systems required to perform those functions at real-world sites. We achieved this by converting MESA-defined logical functions in the manufacturing area into tangible MES. To accomplish this, we divided the functions into specific modules and established the reference architecture as illustrated in Figure 2.

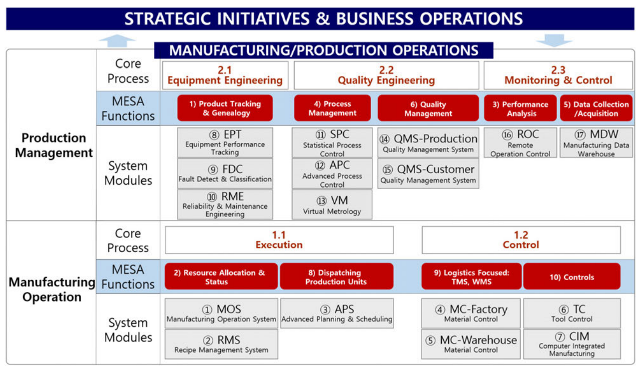


FIGURE 2. 2 dimensions, 5 core process, and 17 system modules & MESA function.

The MESA model extends logical functions to various areas of the enterprise, including business and strategic domains. However, incorporating management information systems (MIS) in measuring MES maturity levels may cause limitations in understanding the focused manufacturing level due to errors caused by averaging industry-specific business processes. Thus, this study has excluded MIS. Conversely, the reference architecture of PSMM is defined by dividing and grouping actual MES utilized in manufacturing plants into module units based on the ten functions of MESA's manufacturing/production operations area. This approach establishes a direction for measuring maturity by determining the contribution of each system module to automating

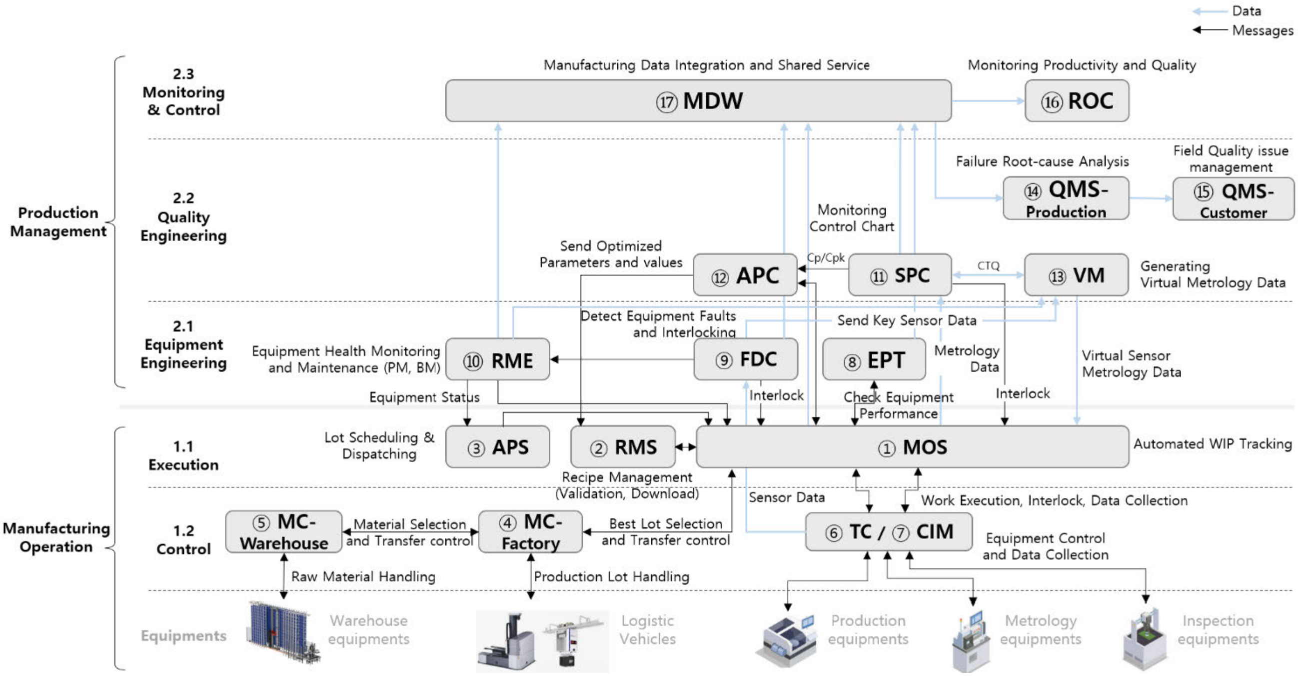


FIGURE 3. **Role and interactions of MES sub-modules according to manufacturing process flow.**

manufacturing process execution. Additionally, labour management is excluded as a diagnostic item among the ten functions, as most companies already use separate commercial systems independent of production automation systems, and a certain level of maturity is standardized.

Thus, by separating and mapping the essential modules of MES used in the real world in conjunction with the nine MESA MES functions, a total of 17 system modules were redefined. These 17 system modules can be classified into two dimensions: manufacturing operation, which directly executes production or collects equipment, process, and quality data; and production management, which utilizes collected data to monitor, analyze, and control equipment efficiency, process anomalies, product quality defects, and productivity.

The manufacturing operation dimension is categorized into two core processes, as execution and control, while the production management dimension is categorized into three core processes as equipment engineering, quality engineering, and monitoring & control. Hence, we aimed to measure the maturity balance considering the interaction between dimensions by placing the production system in two dimensions with detailed module units. The PSMM reference architecture was established with 2 dimensions, 5 core processes, and 17 system modules. Table 2 describes the functions of all system configuration modules.

3) ROLES AND INTERACTIONS OF MES SUB-MODULES

The interactions between the 17 sub-modules defined in the MES Reference Model are shown in Figure 3. In a manufacturing plant, production flows through these 17 physical subsystems, with each MES module performing a specific role.

Material control (MC)-Warehouse automatically transports raw materials from the warehouse to the manufacturing plant for production. MC-Factory handles material logistics and uses advanced planning and scheduling (APS) to determine the equipment and scheduling for each production lot. The manufacturing operation system (MOS) manages production automation by providing input commands to the equipment based on APS information. The recipe management system (RMS) manages equipment recipes, ensuring proper application of recipe parameters.

Fault detection and classification (FDC) monitors real-time equipment parameter values during the process to identify anomalies. Equipment performance tracking (EPT) monitors equipment performance and efficiency. Reliability and maintenance engineering (RME) enhances equipment reliability, availability, and maintainability through systematic analysis and maintenance strategies. Recent research offers valuable insights into predictive maintenance strategies for manufacturing systems [21], [22].

Statistical process control (SPC) measures processed lots to ensure they are anomaly-free and manages the measured values statistically. If the measured values deviate from control limits, advanced process control (APC) automatically adjusts the equipment processing parameters, ensuring product quality compliance. Data collected from FDC, SPC, and other sources are reprocessed as virtual parameters using virtual metrology (VM), enabling monitoring and reuse in production.

Manufacturing data is stored and managed in a repository via the manufacturing data warehouse (MDW). Remote operation control (ROC) oversees overall equipment efficiency and comprehensive production indicators, enabling remote

TABLE 2. Description of functions for 2 dimensions, 5 core process, and 17 system modules.

1. Manufacturing Operation

1.1 Execution

① Manufacturing operation system (MOS)

Shop Floor Control module of MES that processes various business logic during the production process and controls the flow of processes for all stages, from product input on the manufacturing line to shipment.

② Recipe management system (RMS)

A system that manages the processing conditions (recipe) of equipment for each product as data, automatically sets and executes equipment according to the production product, responds to production automation, and improves equipment operation quality.

③ Advanced planning and scheduling (APS)

A Scheduling and Dispatching module of MES that establishes production schedules for product manufacturing and selects the optimal lot/equipment that can be input at each process stage during production to maximize efficiency.

1.2. Control

④ Material control (MC)-Factory

Material control system (MCS) is a control system for unmanned automation of manufacturing processes, that manages logistics equipment (e.g., AMR, AGV, OHT, buffer, stocker) for automated transportation of manufacturing logistics within the manufacturing plant, real-time monitoring, and optimization of transportation routes.

⑤ MC-Warehouse

Warehouse control system (WCS) is an automated control system used within manufacturing or distribution warehouses for logistics handling automation. It manages logistics equipment control and real-time monitoring and enables warehouse automation for receipt and storage control, inventory management and replenishment, and delivery and picking.

⑥ Tool control (TC)

A standard interface for equipment automation that collects/transmits equipment data online and delivers control commands from the upper system (MES).

⑦ Computer integrated manufacturing (CIM)

A basic interface for online data reporting and system linkage control based on equipment online.

2. Production Management

2.1. Equipment Engineering

⑧ Equipment performance tracking (EPT)

A system that monitors and improves equipment operation and production efficiency using equipment status, alarm, and detailed action event data.

⑨ Fault detection and classification (FDC)

A system that maximizes equipment operation rate by collecting/analyzing various sensor data generated by equipment and detecting/classifying equipment faults and anomalies, thereby preventing equipment failures and product quality anomalies in advance.

⑩ Reliability and maintenance engineering (RME)

A system for efficiently managing equipment through operation information linkage and analysis, ensuring process visibility in equipment maintenance management at work sites, and performing main data management, maintenance, and spare parts procurement.

2.2 Quality Engineering

⑪ Statistical process control (SPC)

A system that collects/analyzes inspection/measurement data generated during processes, automatically detects process status changes and deviations and improves process quality.

⑫ Advanced process control (APC)

A process automatic control system that maintains optimal process conditions by adjusting/controlling equipment and conditions (recipe, variables) to minimize process/product quality variability (dispersion) using process inspection/measurement data.

⑬ Virtual metrology (VM)

A system that creates a model predicting quality (measurements or defects) from equipment data and virtually inspects, measures, and monitors the quality of all products in real time without affecting productivity through this model.

⑭ Quality management system (QMS)-Production

A comprehensive analysis system for the cause-and-effect relationship between various production factors (materials, components, equipment, process dispersion, etc.) affecting product quality, measurement, testing, and yield factors in the production process, as well as analyzing the root causes of defects.

⑮ QMS-Customer

A system that comprehensively supports processes such as mass production approval, shipment approval, process dispersion management, reliability evaluation, claims, return approval, and audits to ensure product life, functionality, performance, compatibility, and environmental/standard certification at every stage of the product lifecycle, from development, manufacturing, shipment, customer service, and market for the customer.

2.3 Monitoring & Control

⑯ Remote operation control (ROC)

A real-time monitoring and remote control system for managing comprehensive indicators (KPIs) such as production efficiency, quality, equipment efficiency, and delivery across all production bases.

⑰ Manufacturing data warehouse (MDW)

A data modelling and traceability system for utilizing all structured (numerical, categorical) and unstructured (image, document) data generated throughout the product and process lifecycle, including collection, loading, linkage, analysis, and disposal of data generated in all areas of manufacturing (materials, components, development, equipment, production, quality, shipment, customer, and market).

control. The quality management system (QMS)-Production measures the final quality (good/defective) and combines this data with manufacturing history to identify the cause of quality defects. QMS-Customer handles claims for field quality defects in customer-sold products by providing information on production lot histories and related causes.

Tool control (TC) and computer integrated manufacturing (CIM) serve as intermediaries, connecting product-producing equipment with manufacturing system modules, exchanging commands and data. This detailed framework illustrates how data is collected, analyzed, and used to manage and optimize manufacturing operations, ensuring efficiency and quality throughout the production process.

C. DEFINITION AND OVERVIEW OF PSMM

PSMM assesses the degree of automation in a manufacturing company's MES. It evaluates the system's ability to execute manufacturing without relying on operators and engineers. The model categorizes the 17 MES sub-modules supporting manufacturing execution into two axes: manufacturing operation and production management. It uses a five-level indicator to measure the system's autonomy in performing the five core manufacturing processes without relying on operators and equipment, process, and quality engineers.

The modal aims to objectively compare production systems maturity levels across manufacturing companies. It represents the maturity scores of the 17 system modules as a two-dimensional PSMI for benchmarking purposes. In addition, the model proposes a PSBI to evaluate the balanced development of MES modules, considering the interrelationships between the operation and management axes. This index facilitates the assessment of the overall qualitative maturity of the system.

D. COMPOSITION OF PSMM

PSMM is a comprehensive framework designed to assess and compare the maturity levels of production systems. It comprises three main components: the level classifier (LC), the maturity index (MI), and the balance index (BI). Each of these components plays a crucial role in measuring and comparing the maturity of production systems, as illustrated in Figure 4.

The first component LC measures the maturity of various modules within the MES. The maturity levels are classified into five stages (Lv1-Lv5), with specific criteria defined for each level to evaluate how well the system modules support manufacturing processes. Checklists were developed based on these criteria, allowing system experts to assess the maturity of each module.

The second component, the MI, utilizes the maturity values measured by the LC. The maturity values of each manufacturer's system modules, measured using the LC component, are categorized into two axes: manufacturing operation and production management. For each area, the average maturity values are calculated. These average values are then plotted on a two-dimensional graph, representing the overall maturity of the manufacturer's system as a single point. The overall MI for each manufacturer is determined by averaging the values of the two axes. This provides a comprehensive view of how developed the system is in terms of both operational execution and management capabilities.

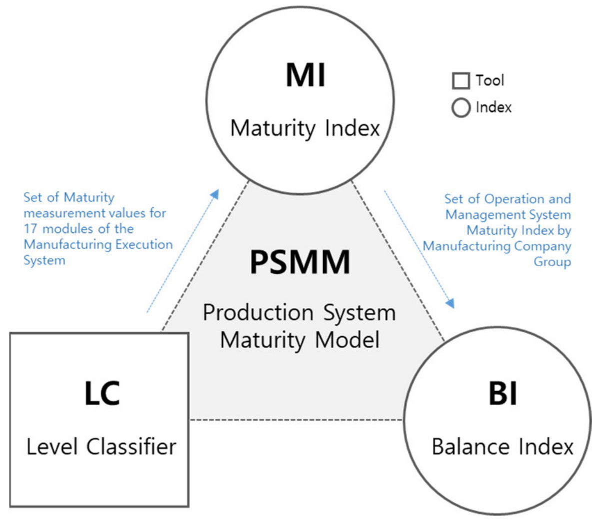


FIGURE 4. Set of operation and management systems.

Finally, manufacturing companies are grouped into clusters based on specific rules. The maturity indices of each cluster are plotted in a two-dimensional space. To evaluate the degree of balanced development between management and operation systems, the BI is defined. This index is calculated by determining the coefficient of determination of the linear regression equation for each cluster.

In summary, PSMM uses objective criteria to evaluate the maturity of MES modules, classifies them into levels, calculates an overall maturity index for manufacturing systems, and assesses the balance between different aspects of the system.

1) LEVEL CLASSIFIER (LC)

The PSMM level classifier establishes maturity criteria for each level, as shown in Table 3. In the manufacturing process, actors are divided into people and systems, and their roles in recognition, decision, and execution are categorized as manual, semi-automatic, fully automatic, and autonomous methods.

The definitions of each method are as follows.

(1) Manual method: A manufacturing operation method where a person is primarily responsible for executing and managing manufacturing processes, utilizing systems to recognize, decide, and execute production situations. This is defined as Lv1 and Lv2.

(2) Semi-auto method: A manufacturing plant operation where the execution and management of manufacturing are carried out with a combination of people and systems, but the system takes on the main role in executing specific sections or processes without relying on operators. This is defined as Lv3.

TABLE 3. Maturity criteria for each stage in the PSMM level classifier.

Maturity Levels		Lv1	Lv2	Lv3	Lv4	Lv5
Operation Types		Manual		Semi-auto.	Full-auto.	Autonomous
Processing Authority	Recognition	Human (using System)	Human (using System)	System	System	System
	Decision	Human	Human	Human (using System)	System, Human	System
	Execution	Human	Human (using System)	System, Human	System	System

(3) Full-auto method: A manufacturing plant operation method that automatically executes and manages manufacturing processes, with human intervention or decision-making limited to specific processes and issues. This is defined as Lv4.
(4) Autonomous method: A self-governing manufacturing plant operation method where the system operates the entire manufacturing execution process and performs automatic control independently. It establishes its own judgment rules by analyzing manufacturing execution data to control critical processes. This is defined as Lv5.

Using these criteria, a level classifier was developed to allow system experts to independently assess the maturity of the current MES. This classifier measures the maturity of 17 MES sub-modules in manufacturing operations and production management.

The LC includes 17 check sheets, each defining operating from Lv1 to Lv5 for each system module (For more information on how system expert groups choose levels, see the Supplementary Material B). The scores range from 1 to 5, with the option to input intermediate levels directly.

2) MATURITY INDEX (MI)

Unlike existing maturity models, the PSMM expands the dimensions of maturity measurement to two axes. The X-axis (manufacturing operation) represents the seven system modules directly involved in production execution, whereas the Y-axis (production management) represents the ten system modules that monitor conditions of equipment, process, quality, and productivity using the performance data collected from these production execution systems, as shown in Figure 5.

The maturity of each individual system on both axes is measured from Lv1 to Lv5. Based on the average scores of each axis, a single point in the two-dimensional space represents the PSMI for each company's MES. This two-dimensional maturity index enables the measurement of the PSBI between operation and management systems.

As shown in Figure 5, the PSMIs of each company are classified into four zones in the two-dimensional space. The boundaries between zones are based on Lv3, where the manufacturing operation method transitions from manual to semi-auto. The characteristics of each zone are given below.

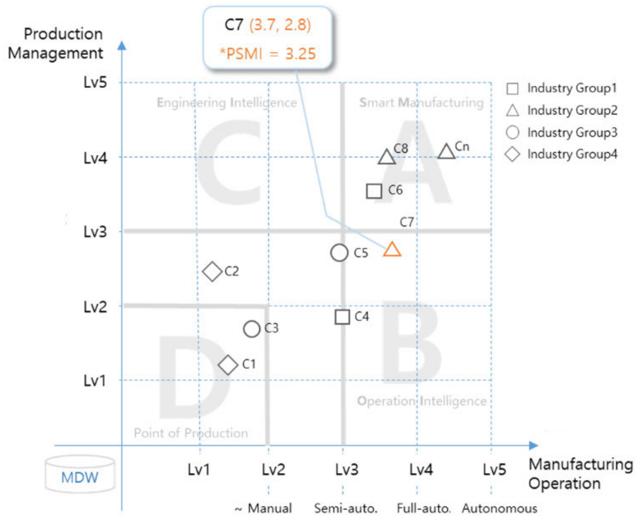


FIGURE 5. Four zones for PSMI.

- *A-zone: smart manufacturing (SM)*
  - A system that automatically executes production and equipment processes, as well as quality control processes centered on systems.
- *B-zone: operation intelligence (OI)*
  - A system centered on production execution automation, combining manufacturing equipment and control recipes.
- *C-zone: engineering intelligence (EI)*
  - A system centered on production management in human-dependent manufacturing equipment and line operations.
- *D-zone: point of production (PoP)*
  - A system that manages point-in-time performance information for progress tracking according to production plans.

As shown in Figure 5, the PSMI of Manufacturer C7 is 3.25 and belongs to the B-zone Operation Intelligence group. The PSMI is calculated as shown in (1).

$$PSMI = \frac{MI_x + MI_y}{2} \tag{1}$$

In (1), MI_x represents the average level score of manufacturing operation system modules, and MI_y represents the average level score of production management system modules.

3) BALANCE INDEX (BI)

BI is an index based on the PSMI that evaluates the balanced maturity of manufacturers' systems regarding operation (X-axis) and management (Y-axis) interdependence. To calculate this index, clusters are extracted according to specific rules, such as industry or company revenue groups (RGs). Linear regression equations are then derived for each cluster, and the coefficient of determination (R^2) is used as the basis for evaluation. When a particular cluster's PSMI achieves balanced development, the PSMIs of that group will appear as a dense distribution around the linear regression line, and the coefficient of determination (R^2) is expected to be close to 1.0. However, if a specific group's MES is developing with a bias towards either the X-axis or Y-axis, the PSMIs of that group are expected to appear as a sparse distribution away from the linear regression line. The PSBI is calculated using (2).

$$PSBI = 1 - \frac{\sum_{i=1}^{n} \left(MI_y - MI_y\right)^2}{\sum_{i=1}^{n} \left(MI_x - \bar{MI}_x\right)^2} \tag{2}$$

BI is crucial for assessing a company's manufacturing performance. As companies expand globally and increase revenue, investing in an advanced MES becomes essential to enhance productivity, cost competitiveness and quality. To optimize production management without relying on human intervention, supporting and collecting relevant functions and data from operation systems is necessary. Implementing a well-planned MES advancement strategy and considering the interaction and balance between system modules on both axes increases the likelihood of successfully implementing data-driven manufacturing DT. One of the main causes of DT failures is the arbitrary collection of performance data from the operation axis, which often lacks the required items and structures for effective management utilisation. Therefore, operation systems need to upgrade their automation level to meet the data item and structural requirements of management systems. Simultaneously, management systems must analyze and utilize this data to implement manufacturing DT, fostering an optimising cycle for both operation and management. PSBI clearly shows the system maturity balance between the operation and management axes, facilitating the pursuit of balanced maturity.

IV. VALIDITY VERIFICATION OF PSMM

A. SELECTION OF PRODUCTION SYSTEM REFERENCE MODEL

To evaluate the validity of PSMM, online and offline surveys were conducted on 364 South Korean and foreign manufacturers from the 12 manufacturing domains defined in the production system reference architecture. The survey sheet consisted of 41 questions, encompassing 7 questions regarding basic manufacturers' information, 17 questions measuring MES maturity, and 17 questions regarding future advancement directions.

Experts responsible for the MES at each manufacturer participated in the survey. They were emailed the maturity evaluation criteria and provided with a URL for the online survey. The evaluation data collected from the participating manufacturers were stored on an online server. The compiled results underwent an initial review and were subsequently explained and confirmed with the manufacturers through email, phone calls, or offline visits before finalization. Table 4 summarizes the investigation and response details.

TABLE 4. Summary of survey and response status.

Investigation Period	1st: '22.10.28~12.05	2nd: '22.12.01~'23.01.31
Subject of Investigation	A total of 364 manufacturing domain companies	
Response/Ratio	93EA	25.55%
Response Status by Industry Group	IG1(Semiconductors, Displays, Batteries):22EA	
	IG2(Home Appliances, Automobiles, Electronics Parts):25EA	
	IG3(Biotech/Pharmaceuticals, F&B, Chemicals):16EA	
	IG4(Machinery, OSAT, Others):30EA	

Data from 93 manufacturers were collected after two investigation periods. The response rate was 25.55%, with balanced data collected across industry groups (IGs). The industry with the highest response rate was IG4(Machinery, OSAT, Others), with 30 responses, followed by IG2(Home Appliances, Automobiles, Electronics parts) with 25 responses. The industry with the lowest response rate was IG3(Biotech/Pharmaceuticals, F&B, Chemicals), with 16 responses.

B. ANALYSIS OF EXPERIMENTAL RESULTS

1) DATA STATUS AND ANALYSIS METHOD

This study utilized data from 93 companies, consisting of responses on 17 system modules. Each manufacturer's 17 system modules were assessed with a maturity score ranging from 1 to 5. PSMI was calculated by averaging the scores on the management and operation axes. Linear regression analysis was conducted on clusters formed based on criteria such as IG and RG for calculating the PSBI. R^2 was used to compare balance indices across clusters. The significance of maturity differences between groups was determined via analysis of variance (ANOVA).

2) ANALYSIS OF MATURITY SURVEY RESULTS

The key questions for understanding the maturity of MES in real-world use by manufacturers, which were the intended outcomes of this experiment, are as follows:

- *Question 1) What is the current level of maturity of MES in the real world, considering the manufacturing domain*

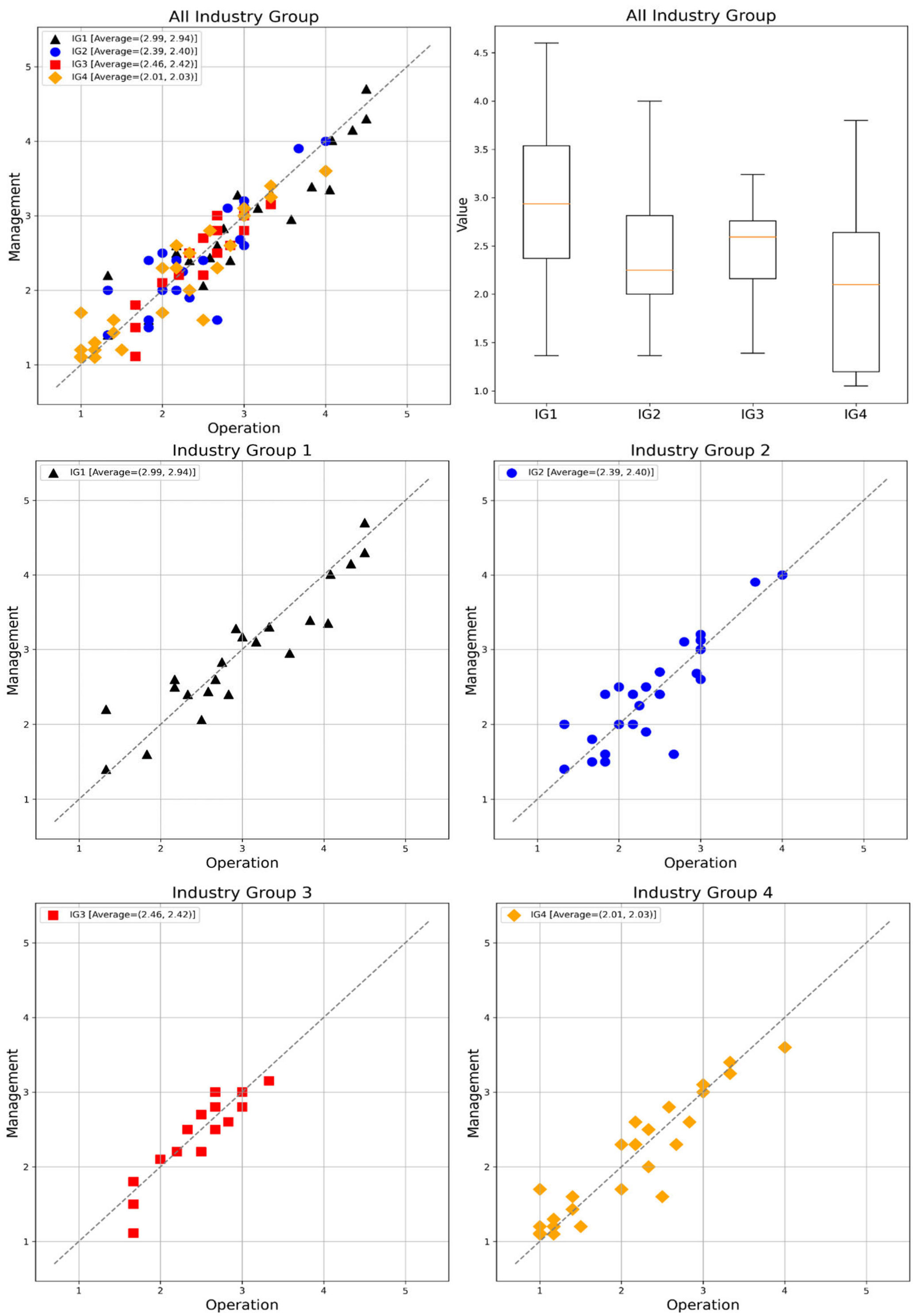


FIGURE 6. Visualization comparison of maturity index by industry group.

TABLE 5. Comparison of maturity index by industry group.

Industry Group	IG1			IG2			IG3			IG4		
	Max	Min	Average	Max	Min	Average	Max	Min	Average	Max	Min	Average
Operation	4.50	1.33	2.99	4.00	1.33	2.39	3.33	1.67	2.46	4.00	1.00	2.01
Management	4.70	1.40	2.94	4.00	1.40	2.40	3.15	1.11	2.42	3.60	1.10	2.03
PSMI	4.60	1.37	**2.97**	4.00	1.37	**2.40**	3.24	1.39	**2.44**	3.80	1.05	**2.02**

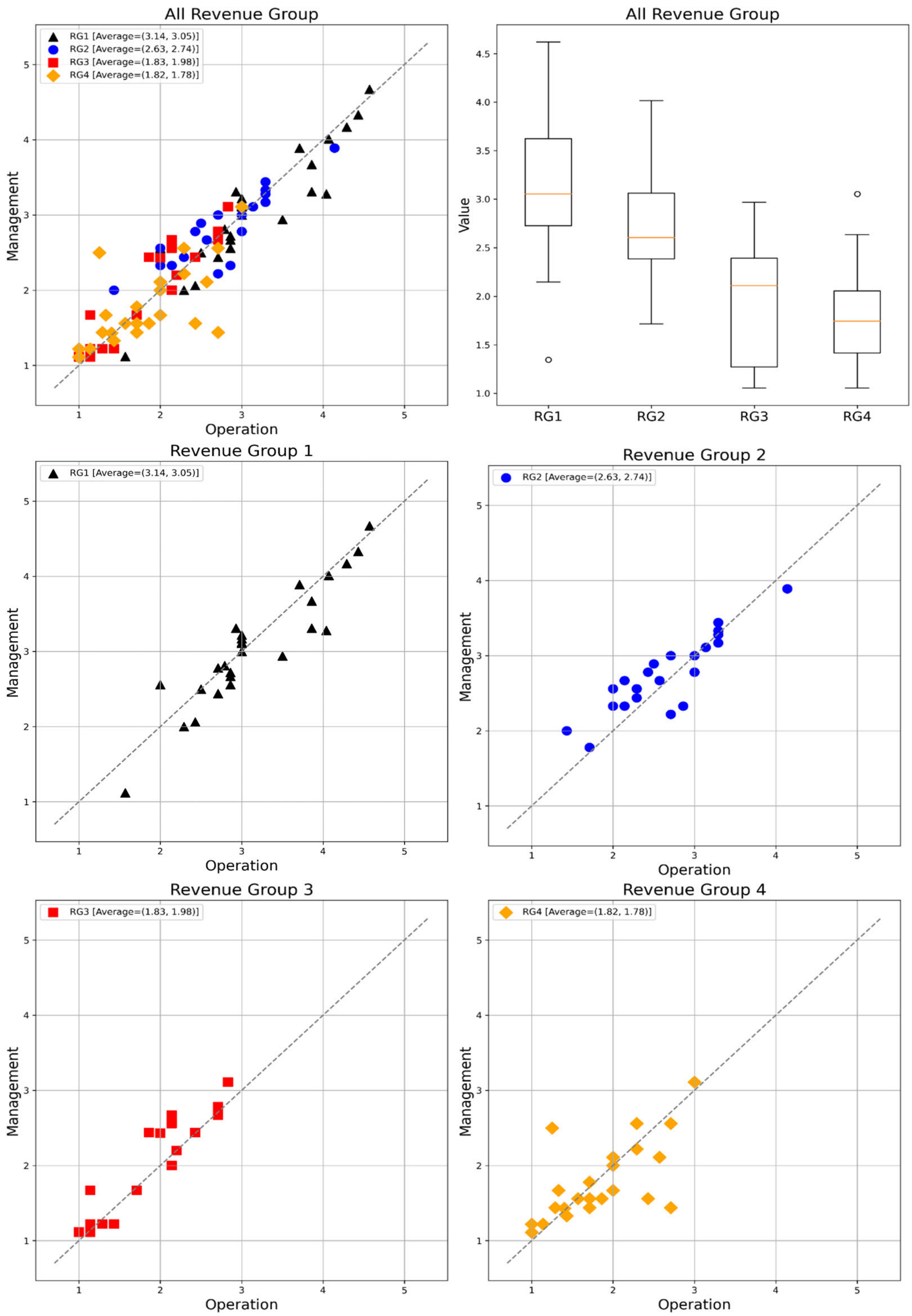


FIGURE 7. Visualization comparison of maturity index by company revenue.

TABLE 6. Comparison of maturity index by company revenue.

Revenue Group	RG1			RG2			RG3			RG4		
	Max	Min	Average	Max	Min	Average	Max	Min	Average	Max	Min	Average
Operation	4.57	1.57	3.14	4.14	1.43	2.63	2.83	1.00	1.83	3.00	1.00	1.75
Management	4.67	1.12	3.05	3.89	1.78	2.74	3.11	1.11	1.98	3.11	1.00	1.72
PSMI	4.62	1.35	**3.10**	4.02	1.72	**2.69**	2.97	1.06	**1.91**	3.06	1.00	**1.74**

and revenue scale? Are there any variations in maturity levels between different groups?

- *Question 2) Are MES achieving balanced development in the operation and management aspects across manufacturing domains and revenue scales?*

Analysis 1-1) Comparison of Maturity by Industry Group
The analysis compares the maturity levels across different IGs. The maturity visualization results for the manufacturing IG are shown in Figure 6, and the statistical values for the PSMI of each group are provided in Table 5.

The average maturity of the MES in IG1, which includes semiconductor, display, and battery production, was the highest at 2.97. This high level of maturity can be attributed to the implementation of automated manufacturing methods that minimize worker intervention in the complex processes of manufacturing advanced components and operating high-precision equipment. On the other hand, IG4, which involves equipment and OSAT manufacturing, had the lowest average maturity at 2.02. This lower level of maturity is due to the presence of smaller revenue-scale manufacturing companies with insufficient automation interfaces supported by manufacturing equipment, leading to lower levels of process control data collection through MES.

The difference in average maturity between IG1 and IG4 was 0.95. We analyzed the ANOVA to verify that there is no difference in maturity index between IG1 and IG4. The ANOVA results indicated a significant difference between the group averages at the 1% significance level, with $F = 15.56$ and $p = 0.0002$. Additionally, the ANOVA results for the null hypothesis of no difference in maturity index across the four IGs showed significant differences in average maturity levels at the 1% significance level ($F = 6.57$, $p = 0.0005$). Specifically, there were no differences between IG2 and IG3 ($F = 0.04$), but significant differences were found between IG1 and IG2 ($F = 6.29$, $p = 0.0158$) and IG1 and IG3 ($F = 4.47$, $p = 0.0415$) at the 5% significance level.

In summary, the overall maturity of MES was high in IG1 due to the use of automated manufacturing processes that reduce the need for worker intervention. Conversely, IG4 exhibited lower maturity levels due to the smaller scale of revenue and a lack of sufficient automation interfaces, which hindered effective process control data collection. The analysis underscores the significant differences in maturity levels among the various industry groups, highlighting the importance of automation and data collection in achieving higher maturity in manufacturing processes.

Analysis 1-2) Comparison of Maturity by Revenue
The maturity levels were compared based on the annual revenue scale of manufacturing companies. Figure 7 displays the maturity of MES for four RGs, while Table 6 presents the statistical values for the PSMI of each group.

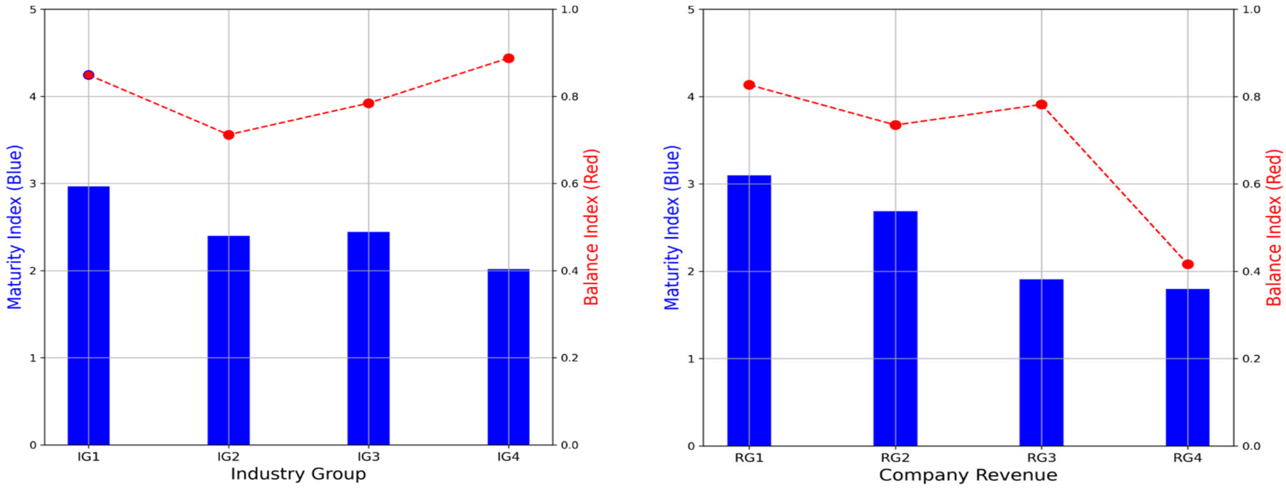
The highest maturity index of MES was observed in RG1, which includes companies with a revenue over 5 trillion KRW, with a value of 3.10. Conversely, the lowest maturity index was found in RG4, which includes companies with a revenue of less than 100 billion KRW, with a value of 1.74. This indicates a substantial gap of 1.36 between the two groups. The ANOVA results for the null hypothesis of no difference in maturity index demonstrate a significant difference between the group averages at the 1% significance level, with $F = 60.24$ and $p = 0.0001$. Furthermore, the ANOVA results for assessing significant differences in the average maturity index of the four RGs yielded $F = 26.99$ and $p = 0.0001$, indicating significant differences between the groups at the 1% significance level.

In conclusion, the survey results reveal a strong correlation between the maturity of MES and the revenue scale of manufacturers. This suggests that larger companies tend to have more mature MES implementations. For small-scale manufacturing companies to achieve meaningful results in implementing smart factories, it is crucial for them to maximize their return on investment by benchmarking the MES implementations of leading manufacturers and identifying the optimal path for advancement. This strategic approach can help smaller companies improve their manufacturing processes and compete more effectively in the market.

Analysis 2) Comparison of Balance Indices by Industry Group and Revenue Group
To achieve successful outcomes through DT in manufacturing companies, it is crucial to collect reliable data from production execution systems within the manufacturing operation domain. Additionally, systems in the production management domain must support automated services for tasks such as equipment operation, process control, and quality improvement. Ideally, a balanced development approach is preferred, satisfying the requirements of the operation axis and management axis. The degree of balanced maturity was analyzed by evaluating the PSBI for each IG and company revenue scale among the participating manufacturers. The results are shown in Figure 8.

Figure 8 on the left displays the PSBI for different IGs independent of the PSMI. Conversely, the right side of the figure shows the PSBI for different RGs. RG1, with a revenue of over 5 trillion KRW, exhibits relatively balanced development with a score of 0.83. However, the index declines from RG2 and sharply drops to 0.49 for RG4, which includes companies with revenue of less than 100 billion KRW. Unlike previous methods that assessed maturity on a single axis, this study employs extended two-dimensional axes, enabling the examination of both PSMI and PSBI. This approach enables more sophisticated interpretations of company value beyond PSMI evaluation. The expanded dimensionality enhances interpretation capabilities and offers additional insights and consulting support regarding a company's maturity level.

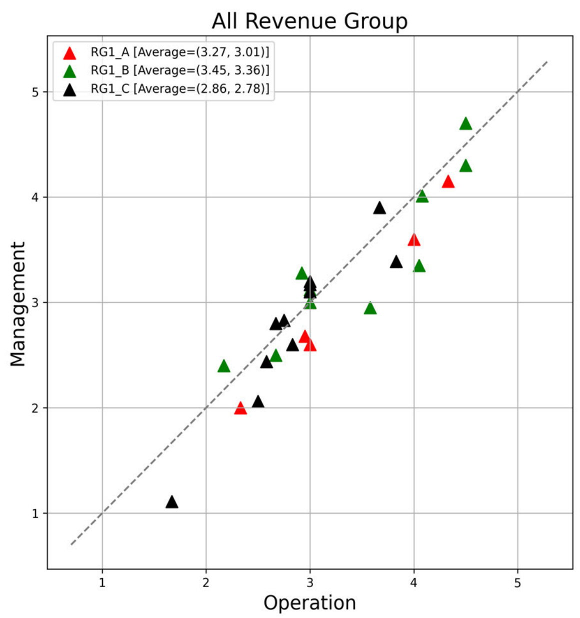
Generally, the balance improves as revenue increases. However, there is an unusual pattern where the balance index sharply rises in RG3 (revenue between 100 billion and 1 trillion KRW) and slightly declines in RG2 (revenue between 1 trillion and 5 trillion KRW). This anomaly can be attributed to the presence of small-scale specialized IT teams in RG3



Industry Group	PSMI	PSBI
IG1	2.97	0.85
IG2	2.40	0.71
IG3	2.44	0.78
IG4	2.02	0.89

Company Revenue	PSMI	PSBI
RG1	3.10	0.83
RG2	2.69	0.73
RG3	1.91	0.78
RG4	1.74	0.49

FIGURE 8. **Balance index analysis results by industry group and company revenue.**



Company Revenue	PSMI	PSBI
RG1_A	3.14	0.81
RG1_B	3.40	0.80
RG1_C	2.82	0.72

FIGURE 9. **Results of RG1 group segmentation (RG1_A: over 80 trillion KRW, RG1_B: over 20 trillion and less than 80 trillion KRW, and RG1_C: over 5 trillion and less than 20 trillion KRW).**

manufacturing companies, which develop and operate MES using commercial solutions while minimizing customization. As companies grow and user scale and requirements diversify, customisation of the MES increases, leading to a partial decline in the balance index. However, the balance index rises again as the company matures and establishes its manufacturing IT structure. Thus, it was confirmed that when the revenue of a manufacturing company increases, investment in enhancing their MES leads to a simultaneous increase in both PSMI and PSBI.

The RG1 group (revenue over 5 trillion KRW), which exhibited the highest PSMI and PSBI values, was further analyzed by segmenting it into sub-groups. These sub-groups were defined as follows: (i) RG1_A (revenue over 80 trillion KRW), 9ii) RG1_B (revenue between 20 and 80 trillion KRW), and (iii) RG1_C (revenue between 5 and 20 trillion KRW). The results for each sub-group are depicted in Figure 9. The PSMI values for the subdivided groups RG1_A, RG1_B, and RG1_C are 3.14, 3.40, and 2.82, respectively. According to the ANOVA results for the null hypothesis of no difference in PSMI ($F = 1.74$ and $p = 0.1977$), there is no significant difference in PSMI levels among the three groups. However, there is a significant difference in index results. This indicates that although the revenue scale does not impact the maturity index for the sub-groups of RG1 (revenue over 5 trillion KRW), it does affect the balance index.

C. KEY FINDINGS

In this experiment using PSMM, we made three significant findings. Firstly, we conducted an MES level diagnosis for 12 manufacturing industry verticals and confirmed a significant gap in maturity indices among the four industry clusters. Advanced component industries like semiconductors, displays, and batteries showed the highest maturity level at 3.10. Many companies in other industries clustered around Lv3 (semi-auto) in the PSMI index. We anticipate that these companies quickly identify the correct path for MES advancement by benchmarking those in Lv4 in the future.

Secondly, middle-standing enterprises with revenue between 500 billion and 1 trillion KRW (RG3) exhibited a significantly high balance index (PSBI=0.78) compared to companies with revenue below 500 billion KRW (RG4). This higher balance index was observed when these middle-standing enterprises adopted packaged MES solutions. However, as these companies grew into enterprises with revenue over 1 trillion KRW (RG2), the balance index (PSBI=0.73) declined due to custom developments required for various business needs. Interestingly, for large corporations with revenue over 5 trillion KRW (RG1), the balance index (PSBI=0.83) increased again after navigating through the customization phase. This pattern was discovered through the balance index.

Thirdly, to achieve tangible results in manufacturing DT, it is necessary to advance to at least the semi-auto state (PSMI = 2.5, PSBI = 0.75). This advancement involves enabling systems in the operation domain to collect meaningful data and having systems in the management domain support automated services for tasks such as equipment operation, process control, and quality improvement.

These findings underscore the importance of benchmarking, the impact of revenue scale on MES balance, and the critical thresholds for successful Digital Transformation in manufacturing.

V. CONCLUSION

A. SIGNIFICANCE AND NOVELTY OF THIS STUDY

In the era of Industry 4.0, MES has evolved from a simple IT tool to a critical infrastructure. Manufacturing companies have focused on enhancing their competitiveness through smart factories and DT. However, there has been a lack of practical tools or methods to objectively assess the current level of MES, which serves as a foundation for these initiatives, and to benchmark against more advanced companies.

The PSMM research aims to address these issues and offers the following significant and distinctive contributions:

- *For the first time, the PSMM enables companies to map the maturity level of each submodule of their MES in a two-dimensional space. This allows them to assess both the PSMI and the PSBI. By diagnosing the MES of 93 companies, differences and development patterns of maturity and balance by industry and revenue scale can be identified.*
- *Significant differences have been identified by examining the companies' IG and RG measurements through two-dimensional axes.*
- *By applying the same maturity assessment model across various industries and companies with different maturity levels, direct comparisons of smart factory maturity levels are enabled. This facilitates mutual benchmarking among companies.*
- *Companies can establish future MES advancement goals and determine specific system configurations required.*
- *Balanced systems development in the operation and management domains is critical for growing companies to enhance equipment operation, process control, and quality through DT, as confirmed by the PSBI.*
- *For the first time, a practical MM model that fully satisfies 9 out of the 10 PSMM or partially fulfils 1 criterion has been presented.*

B. LIMITATIONS OF THIS STUDY AND DIRECTIONS FOR FURTHER RESEARCH

The research on the MES maturity assessment model presented in this study has certain limitations that should be acknowledged. Firstly, the study focused on measuring absolute maturity levels using the same criteria and did not address the need for industry-specific or revenue-scale-based guidelines to determine appropriate maturity levels or further advancement. Consequently, it did not explore why companies struggling with DT have low maturity levels, highlighting the need for future research to identify priority system modules for improvement.

Moreover, while the study diagnosed the levels of each system module for the five core processes, it did not provide a detailed breakdown of the required functions within each module. Future research should analyze the characteristics and differences between companies at different maturity levels to identify functional gaps and determine which modules should be prioritized for enhancement.

Further research is necessary to establish a methodology for sequential enhancement, prioritizing specific modules. Ultimately, the aim is to develop a tailored and efficient MES advancement methodology for the manufacturing operation and production management domains, considering individual company characteristics. This research will provide detailed guidelines for each system module, enabling companies to implement smart factories based on their specific circumstances.

In summary, the study's limitations highlight the need for a more nuanced approach that considers industry-specific and revenue-scale-based guidelines, detailed functional breakdowns of system modules, and sequenced enhancement methodologies. Addressing these areas in future research will provide a comprehensive framework for companies to effectively advance their MES and achieve successful digital transformation.

APPENDIX A
EXISTING MMs IN MANUFACTURING DOMAIN

See Table 7.

APPENDIX B
FITNESS EXISTING MMs BASED ON PSMM 10 CRITERION

See Table 8.

TABLE 7. The existing MMs in manufacturing domain.

MM#	The MM	Reference
MM01	The connected enterprise maturity model	[23]
MM02	The digital maturity model 4.0	[24]
MM03	IMPULS – Industrie 4.0 readiness	[25]
MM04	A maturity model Industry 4.0 readiness	[16]
MM05	System integration maturity model Industry 4.0 – SIMMI 4.0	[26], [27]
MM06	Industrie 4.0 maturity index – Acatech	[28]
MM07	DREAMY – Digital readiness assessment maturity model	[29], [30]
MM08	Three-stage maturity model in SMEs toward Industry 4.0	[31]
MM09	A digital maturity model for telecommunications service providers	[32]
MM10	Industry 4.0 – MM	[33], [34]
MM11	A smart manufacturing maturity model for SMEs (SM3E)	[35]
MM12	DPMM 4.0 – Industry 4.0 maturity model for the delivery process in supply chains	[36]
MM13	Maturity and readiness model for Industry 4.0 strategy	[37]
MM14	A preliminary maturity model for leveraging digitalization in manufacturing	[38]
MM15	A critical review of smart manufacturing & Industry 4.0 maturity models: Implications for small and medium-sized enterprises (SMEs)	[39]
MM16	Digital Twin in manufacturing: A categorical literature review and classification.	[40]
MM17	A survey of the advancing use and development of machine learning in smart manufacturing.	[41]
MM18	A model for assessing the maturity of Industry 4.0 in the banking sector	[42]
MM19	IMA – Infrastructure maturity assessment	[43]
MM20	A maturity assessment approach for conceiving context-specific roadmaps in the Industry 4.0 era	[44], [45]
MM21	Roadmapping toward industrial digitalization based on an Industry 4.0 maturity model for manufacturing enterprises	[18]
MM22	Development of manufacturing execution systems in accordance with Industry 4.0 requirements: A review of standard-and ontology-based methodologies and tools.	[15]
MM23	The digital transformation capability maturity model (DX-CMM)	[17], [46]
MM24	Intelligent manufacturing execution systems: A systematic review	[47]
MM25	Maturity assessment for Industry 5.0: A review of existing maturity models	[6]

TABLE 8. Results of fitness existing MMs based on PSMM 10 criterion.

* Support (1), Partially Support (0.5), Not Support (0)

MM#	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	Fitness (0~10)
MM01	0	0.5	1	0	0	0	0	0	0	0	1.5
MM02	0	0.5	1	0	0	0	0	0	0	0	1.5
MM03	1	0	1	0	0	0	0	0	0	0	2.0
MM04	1	0	1	0	0	0	0	0	0	0	2.0
MM05	1	0	1	0	0	0	0	0	0	0	2.0
MM06	0	0.5	1	0	0	0	0	0	0	0	1.5
MM07	1	0	1	0	0	0	0	0	0	0	2.0
MM08	1	0.5	1	0	0	0	0	0	0	0	2.5
MM09	1	0.5	0	0	0	0	0	0	0	0	1.5
MM10	1	0	1	0	0	0	0	0	0.5	0	2.5
MM11	1	0.5	1	0	0	0	0	0	0	0	2.5
MM12	1	0.5	0	0.5	0	0	0	0	0	0	2.0
MM13	1	0.5	0	0.5	0	0	0	0	0	0	2.0
MM14	1	0.5	1	0.5	0.5	0	0	0	0	0	3.5
MM15	1	0.5	1	0.5	1	1	0.5	0	0.5	0	6.0
MM16	1	0.5	0	0	0	0	0.5	0	0.5	0	2.5
MM17	1	0.5	0.5	0	0	0	0	0.5	0.5	0	3.0
MM18	1	0	1	0.5	0.5	0	0	0	0	0	3.0
MM19	1	0	1	0.5	0.5	0	0	0.5	0	0	3.5
MM20	1	0	1	0.5	0.5	0	0	0.5	0	0.5	4.0
MM21	1	0	1	0.5	1	0	0	0.5	0.5	0.5	5.0
MM22	1	1	1	1	1	1	0.5	0	1	0	7.5
MM23	1	1	1	1	1	0.5	0.5	0.5	1	0.5	8.0
MM24	1	1	1	1	1	1	0.5	0	1	0	7.5
MM25	1	1	0.5	0.5	0	0.5	1	0	1	0	5.5

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DAE-JUNG AHN received the B.S. degree in computer science and statistics from Hanshin University, in 1999, and the M.S. degree in electronic engineering from Kyung-Hee University, in 2009. He is currently pursuing the Ph.D. degree in industrial and management engineering with Korea University. In 1991, he started his career as a DRAM Process Architect at the Semiconductor Memory Division, Samsung Electronics, and performed failure analysis and statistical yield data analysis for nine years. Since 2000, he has researched the yield management system (YMS) for wafer yield enhancement in the manufacturing execution system (MES) team for 12 years. In 2012, he moved to Samsung SDS and has been carrying out the next-generation MES development project for Samsung OLED Display, Mobile Phones, CE, MLCC, and secondary battery manufacturers for 12 years. His research interests include manufacturing equipment fault detection and classification (FDC), YMS, and fully automated digital manufacturing systems.

CHANGDONG JUN received the B.S. degree in chemical engineering from Hanyang University, in 2002, and the M.S. degree in industrial and management engineering from Korea University, in 2018, where he is currently pursuing the Ph.D. degree in industrial and management engineering. In 2002, he started his career as a Dry Etch Process Engineer at the Semiconductor Memory Division, Samsung Electronics. He successfully set up and mass-produced semiconductor memory processes ranging from the world's first 90 nm to 60 nm memory chips. In 2011, he transitioned to a systems software engineer role, researching control logic for APC, FDC, SPC, and VM systems, and applying them to actual production within MES systems. In 2021, he moved to LG CNS and currently works at LG Energy Solution and LG Innotek, designing application architecture in manufacturing systems and standardizing and optimizing APC, FDC, and SPC systems.

SEUNGHWAN SONG received the B.S. degree in information statistics from Korea University, in 2019, where he is currently pursuing the M.S. and Ph.D. degrees in industrial and management engineering. His research interests include representation learning and prognostics and health management in manufacturing. He is conducting research to improve manufacturing systems using the latest deep learning technologies.

JUN-GEOL BAEK received B.S., M.S., and Ph.D. degrees in industrial engineering from Korea University, in 1993, 1995, and 2001, respectively. From 2002 to 2007, he was an Assistant Professor with the Department of Industrial Systems Engineering, Induk University, Seoul, South Korea. From 2007 to 2008, he was also an Assistant Professor with the Department of Business Administration, Kwangwoon University, Seoul. In 2008, he joined the School of Industrial and Management Engineering, Korea University, where he is currently a Professor. His research interests include fault detection and classification (FDC), advanced process control (APC), prognostics and health management (PHM), and big data analytics in manufacturing.