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RESEARCH ARTICLE

Success Factors of the Adoption of Smart Factory Transformation: An Examination of Korean Manufacturing SMEs

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ABSTRACT A smart factory is a fully automated production system enabled with novel digital technologies. Numerous studies consider its emergence as the arrival of a new wave of production innovation. However, research is scant on why its adoption rate has lagged behind the expectations of investors and policymakers. Thus, this study examined the effect of top management support for information systems, the existing production systems, the perceived usefulness of smart factories, and outsourcing experiences on firms' intention to adopt smart factories. Using the data of 1,067 Korean manufacturing small and medium-sized enterprises and structural equation modeling, this study finds that the performance of the existing production systems significantly increases the benefits expected from smart production systems, thus strengthening firms' intention to adopt smart factories. It also finds that the top management's support for information systems does not have a significant impact on the benefits expected from smart production systems. Furthermore, the overall mechanism of smart factories' adoption is strengthened when firms develop their production systems in-house. The results of this study provide useful insights for practitioners seeking to transform traditional production systems into smart factories. They also provide a strategic guideline regarding outsourcing experiences.

INDEX TERMS Industry 4.0, Korean SMEs, smart factory, smart factory transformation, smart production system, structural equation modeling, top management support.

I. INTRODUCTION

Ever since the term "Industry 4.0" was first introduced at the Hannover Fair in 2011 [1], [2], it has drawn a lot of attention from academia and industry. This novel concept encompasses computerizing the manufacturing industry [2] and automating production processes through digitalization and the use of new and advanced technologies [3]. Some researchers call it the fourth industrial revolution, which consists of cyber-physical systems, the Internet of things (IoT), and other smart systems providing enhanced interaction and connectivity [4], [5]. Thus, Industry 4.0 is expected to revolutionize manufacturing [6].

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When the key components of Industry 4.0 are successfully implemented and integrated, the resulting product is a smart factory [3]. In a smart factory, all components and equipment are interconnected and digitalized via information and communication technologies and production technologies [7]. These factories can rapidly adapt to changes, automatically optimize the production process, and achieve smart cyber-physical production systems [8], [9], [10]. Radziwon et al. [11] stated that a smart factory is a manufacturing solution that makes production processes flexible and adaptable, solving manufacturing problems arising from rapidly changing boundary conditions. Meanwhile, Gartner [12] defined a smart factory as the utilization of different combinations of modern technologies to make production capability highly flexible and self-adapting. With smart factories, employees can continuously monitor production processes and save time and costs [13]. Notably, Deloitte [14] estimated that smart factories can increase asset utilization by 20%, save expenses by 30%, and improve product quality by 30%. Thus, it is expected that the manufacturing sector will transform its existing production systems into smart factory systems owing to the emergence of Industry 4.0 [6].

Although the concept of "smart factories" was introduced a long time ago, its adoption rate has yet to meet the expectations of investors and policymakers. This situation is particularly evident in Korea. In 2014, the Korean government announced a manufacturing innovation strategy that urged businesses to adopt the smart factory production system. Resultingly, by 2017, 5,003 factories of small and medium-sized enterprises (SMEs) were successfully transformed into smart factories [15]. Following this achievement, the government set a new target in 2018: to convert 30,000 factories into smart factories by 2022 [15]. However, the implementation rate has reached only 66%, with merely 19,799 factories finishing the transformation by August 2022 [16]. Despite the government's extensive financial and policy support, Korean SMEs did not actively adopt smart factories [17].

This stunted adoption of smart factories may be due to the absence of support for SMEs. The introduction of new technologies is often the cause of strong resistance in SMEs that have limited resources [18], [19], [20]. This is because employees have differing views on whether new technologies are beneficial and their effect on work [21]. A similar resistance exists over the introduction of smart factories [17], [22]. Currently, many countries are switching to smart factories to promote manufacturing innovation [17]. However, as stated earlier, this switch is not occurring in Korea as quickly as anticipated. To facilitate the transformation of existing factories into smart ones and hasten the fourth industrial revolution, it is imperative to identify the determinants of the adoption of smart factories.

Thus, this study explores the mechanism of adopting a smart factory to determine the factors influencing its adoption and create a favorable opinion of these factories among Korean SMEs. Implementing a smart factory system is closely associated with using manufacturing information systems, such as enterprise resource planning (ERP), supply chain management (SCM), and manufacturing execution system (MES) [2], [3], [23]. Therefore, this study particularly analyzes how top management support for information and production systems and the performance of the current information and production systems affect SMEs' intentions of adopting smart factories. In addition, this study tests whether a difference exists in SMEs' acceptance of smart factories based on their experiences of outsourcing. This is because, as many SMEs outsource services when developing or implementing new information systems, outsourcing can cause unexpected difficulties [24], [25], [26], [27]. This study makes a significant contribution to the literature because it empirically examines the overall process of introducing smart factories. Most previous studies have presented either conceptual analyses or case studies. More specifically, this study intends to address the following research questions (RQs).

RQ1: What are the determinants of Korean SMEs' intention to adopt smart factories?

RQ2: How does the current production system influence the adoption of smart factories?

RQ3: How do in-house and outsourcing experiences influence SMEs' intention to adopt smart factories?

The remainder of this paper is structured as follows. Section 2 discusses the theoretical background and presents the proposed hypotheses. Section 3 explains the research methodology. Section 4 presents the empirical results. Finally, Section 5 covers the implication of the results, the study's limitations, and directions for future research.

II. THEORETICAL BACKGROUND AND HYPOTHESES DEVELOPMENT

A. TOP MANAGEMENT SUPPORT AND THE EXPECTED BENEFITS OF SMART PRODUCTION SYSTEM

To identify success factors that lead to the adoption of smart factories, this study focuses on the top management's support for information systems. Top management support refers to the degree to which the top management commits and prioritizes activities to obtain the time and financial resources needed for transforming the production system in support of the business strategy [28], [29]. High levels of top management support for production systems reflect top managers' high interest and investment in integrating advanced information technologies with existing resources and operations to achieve better manufacturing performances [30].

In the context of manufacturing systems in Industry 4.0, various articles have emphasized the importance of management support. Hecklau et al. [31] highlighted the role of management support in mitigating challenges and developing core competencies in the automation of manufacturing processes. Kamble et al. [32] identified high implementation cost as one of the main barriers to the adoption of Industry 4.0. To achieve technical competency, firms must obtain financial resources to develop an appropriate infrastructure or adopt to IoT handle real-time data. Based on the SMEs in Malaysia and Iran, Ghobakhloo [33] identified that the top management's support not only enables daily activities but can also help gain a competitive advantage in the industry through smart manufacturing-related information and digital technologies.

However, recent studies on the adoption of smart production with digital competencies emphasized the importance of a detailed understanding of the top management's role in the overall benefits of smart production systems [33], [34]. Thus, this study focuses on the expected performance, or performance expectancy, measured by the degree to which a firm believes that using new technologies or products will support and facilitate employees in increasing their capabilities [35]. Since the smart factory is a new system that innovates manufacturing and operations, firms generally anticipate that it will improve their overall performance [36]. Based on these arguments, the following hypothesis is posited.

H1: The top management's support for information and production systems is positively associated with the expected benefits of smart production systems.

B. TOP MANAGEMENT SUPPORT AND THE PERFORMANCE OF EXISTING PRODUCTION SYSTEMS

In addition to introducing new systems such as smart production systems, the top management's support affects the use and performance of existing production systems. In the recent trend of production systems and their transformation paradigm, various articles highlight the importance of the management's support for information systems and its commitment to overall performance [37], [38], [39]. For example, the higher the chief executive officer's (CEO's) interest and support, the easier it is to obtain the required resources, and the higher the cooperation among different functions to meet the needs of information system users [40]. Furthermore, the top management and its capacity to coordinate and integrate knowledge contribute to complex manufacturing stages [34]. In particular, CEOs of SMEs significantly influence the firm's attitude [41], [42], thus increasing the importance of top management support.

Evidently, the top management's support is paramount for the optimal performance of production systems because its interest in information technology-based production and service facilitates the establishment of related plans and strategies. Moreover, it verifies alignment with management objectives through investment and evaluation of the applicability of information systems [43]. Various studies have shown that the top management's support determines the performance of information systems and technologies [44], [45], [46]. Providing more evidence, Lin et al. [47] recommended including top management support as a dynamic capability that positively affects manufacturing enterprises' operation.

Overall, the performance of existing production systems depends on resource allocation and the intensity level allowed by the top management or stakeholders. The development of production systems involves advancing the existing information systems, such as ERP, MES, and product lifecycle management (PLM) [2], [3], [23]. Moreover, if the top management intends to use knowledge management systems that handle real-time data or big data, any changes or improvements made to the information system are likely to enhance the performance of production systems [38], [48], [49]. This argument aligns with existing findings that the top management's involvement is crucial to driving the value of production systems [22], and the lack of top management support can lead to the failure of new information and production systems [50]. Based on these arguments, the following hypothesis is proposed.

H2: The top management's support is positively associated with the performance of the existing production systems.

C. ROLE OF CURRENT PRODUCTION SYSTEMS IN THE ADOPTION OF SMART FACTORY TRANSFORMATION

The scope of production and operations management has significantly expanded owing to the application of information technology and systems [51]. These days, firms use various information and production systems to manage manufacturing and production more efficiently [52], [53], [54]. ERP, SCM, MES, and PLM are some examples of such systems.

A combination of information and manufacturing technologies make up smart factories [55], [56]. More precisely, a highly connected and digitalized manufacturing system is built by combining advanced information technologies, such as IoT, big data, and cloud computing, with the existing production systems. Haddara and Elragal [2] stated that the ERP system is the backbone of Industry 4.0 and the implementation of a smart factory. Interviews and video conferences demonstrate that the ERP system in Greek companies is well prepared to transform the existing factories into smart factories. Similarly, Padhi [23] asserted that it is important to build systems such as ERP, MES, and PLM in his five-step practical approach to building smart factories. Sufian et al. [3] also highlighted the importance of current information systems in the successful implementation of smart factories. They also emphasized that information technologies, such as ERP and MES, connect different departments and facilitate their acquisition of operational data. This notion aligns with Mladineo et al. [57], who discovered that implementing the "smart factory" concept requires the integration of MES and ERP. Therefore, information systems such as ERP, MES, SCM, and PLM should be integrated to successfully develop smart factories [53], [58], [59]. All these arguments indicate that the existing information and production systems play a critical role in the adoption of smart factories.

If companies can clearly observe the benefits of using production systems, they may expect fewer barriers and better performance from the adoption of smart factories. Several studies have examined the positive impact of the performance expected from the new technology as a determinant of new technology adoption. They found that companies that expect high benefits are likely to have a favorable opinion of smart factories [32], [35]. This may be because some factors directly influence the adoption of new technologies, but there are some circumstances in which their acceptance is determined based on the benefits expected from their introduction [38], [39], [60]. Specifically, clear comprehension and perceived usefulness of IoT's benefits mitigates the expected implementation cost, thereby increasing the intention to transform the production system [28], [32]. Similarly, this study applied the expected benefits and intention to introduce smart factories separately.

Some studies have examined these relationships in the context of smart factories. Won and Park [17] empirically analyzed the effect of perceived benefits, organizational readiness, and the external pressure to adopt smart factories. They discovered that perceived benefits positively affect the implementation of smart factories, and organizational support positively influences the decision of adopting these factories. Similarly, Jo [28] showed that perceived usefulness is a critical determinant of the intention to adopt smart factories. Based on these arguments, this study develops the following three hypotheses.

H3: The performance of the existing production systems is positively associated with the expected performance of smart production systems.

H4: The expected benefits of smart production systems are positively associated with the intention to adopt smart factories.

H5: The performance of the existing production systems is positively associated with the intention to adopt smart factories.

D. IMPACT OF OUTSOURCING EXPERIENCE

According to Clark et al. [61] and Gonzalez et al. [24], information systems outsourcing (ISO) refers to when an organization enters into a contract with a specialized external firm, entrusting it to provide the physical and human resources required for its information systems in exchange for some remuneration. ISO originated in 1989, when Eastman Kodak outsourced its computer room and human resources to IBM to enhance competitiveness by reducing costs [62]. Since then, ISO has become a common practice directly related to businesses' long-term performance and survival. Moreover, outsourcing information systems increases efficiency and reduces costs in the short term [63].

As a result, extensive research has been conducted on ISO. Studies have mainly explored the motivation, scope, performance, and decision-making in ISO, along with the type of contracts and partnerships [64], [65], [66], [67]. However, only a few studies have investigated how ISO affects the process of introducing new systems, such as smart factories.

Regarding the role and performance of ISO, many researchers only analyzed its impact on system effectiveness, user satisfaction, job satisfaction, quality of service, and cost reduction [25], [68], [69], [70], [71]. Among them, Gorla and Somers [71] studied the performance of user situations and paid services depending on the extent of information system outsourcing. Attewell [72] found that ISO acts as a mediator in overcoming internal limitations and helps implement an effective information system.

However, these studies did not identify the role of ISO in the implementation of a new information system such as a smart factory. Examining the part that outsourcing plays in putting a new digitalized manufacturing system into place can help determine effective ways of introducing a smart factory. Therefore, this study proposes the following hypothesis to ascertain an effective strategy for developing smart factories. It assumes that companies that have used outsourcing to create information systems in the past will likely do the same when adopting smart factories.

H6: The mechanism of adopting smart factories varies depending on the firm's outsourcing experience.

Fig. 1 illustrates the research model.

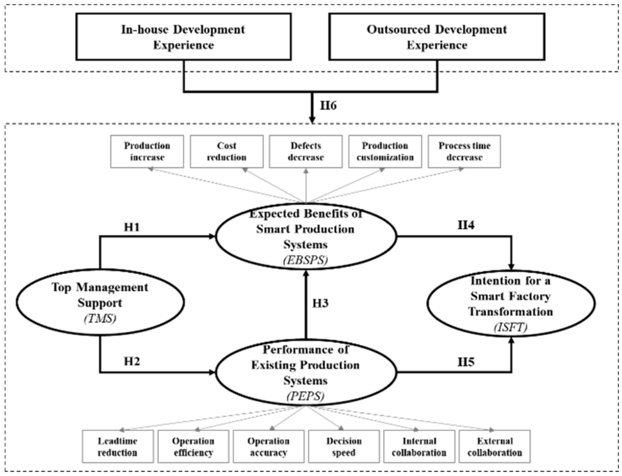

FIGURE 1. Proposed model for transforming factories into smart factories.

III. METHODOLOGY

A. DATA COLLECTION

Data were collected from the Survey on the Information Level of Korean Small and Medium Enterprise, which was conducted in 2019 by the Korean Ministry of SMEs and Startups. This data can be considered objective and unbiased because a government agency investigates the current status of all companies registered in the department across all industries. Another advantage it that this public data is highly reliable to use for research. Above all, the quality of research has improved because it used a wide range of data that are difficult to obtain from individuals or research institutes. A total of 2,691 Korean manufacturing SMEs responded to the survey. However, the responses of those companies that had already implemented the smart factory system or did not answer about the expected performance of smart production solutions were excluded. Resultingly, the data of 1,067 companies were obtained. Table 1 summarizes the characteristics of these companies. Evidently, they were evenly distributed between the companies founded before 1990, those founded between 2000 and 2010, and those founded after 2010. Nearly 80% of the companies had annual sales of less than USD 38.5 million, and 74.7% had fewer than 100 employees. Table 2 shows the distribution of companies based on their industry. It shows that 1,067 companies were distributed across 23 manufacturing industries, which are categorized based on the Korean Standard Classification of Occupations standard developed by Statistics Korea. These findings show that a wide range of Korean manufacturing SMEs were included in this study's sample.

B. INSTRUMENT DEVELOPMENT

Four conceptual constructs were developed in this study. Table 3 summarizes the indicators used to measure the individual constructs. First, two indicators were used to measure "Top Management Support (TMS)," which is the degree of interest and support the top management exhibits toward the firm's information systems. Second, the "Expected Benefits of Smart Production System (EBSPS)" refers to the benefits

TABLE 1. Profile of the responding companies.

General Information		Frequency	%
Date of establishment	Before 1990	190	17.81
	1990s	261	24.46
	2000–2004	195	18.28
	2005–2009	170	15.93
	After 2010	251	23.52
Number of workers	1–9	347	32.52
	10–19	6	0.56
	20–49	257	24.09
	50–99	187	17.53
	100–299	198	18.56
	300–999	64	6.00
	1000 ≤	8	0.75
Annual Sales in USD*	< 20 million	707	66.26
	20–38.49 million	120	11.25
	38.5–299.99 million	220	20.62
	300–499.99 million	11	1.03
	500–999.99 million	6	0.56
	1 billion ≤	3	0.28

Note: Annual sales were first investigated in KRW, then converted to USD using the average exchange rate in 2019, which was 1165.65.

expected from the firm's production system if it adopts a smart factory. Five indicators were used to measure this construct. Third, the ''Performance of Existing Production Systems (PEPS)'' represents the degree to which the firm's existing information and production systems contribute to improving its performance. It was measured using six indicators. Finally, the ''Intention of Smart Factory Transformation (ISFT)'' was measured using a single indicator because the respondents were directly asked about their intentions of developing a smart factory. All indicators were measured using a five-point Likert scale. The responses to the ISFT indicator were measured based on the firm's degree of preparation for developing a smart factory (5 = the firm has prepared a comprehensive plan to introduce a smart factory in the near future, 3 = there is no concrete plan, but the firm strongly intends to introduce a smart factory, 1 = there is no immediate plan for or an interest in introducing a smart factory).

IV. RESULTS

A. RELIABILITY AND VALIDITY OF THE MEASUREMENT MODEL

A confirmatory factor analysis was conducted using AMOS 22.0 to examine the convergent and discriminant validities of measures. The chi-square value (χ^2) of the model was 393.793, and the degree of freedom was 62. The p-value of the chi-square test was less than 0.05. Since using the chi-square test presents some limitations [77], the goodness-of-fit was determined using other measures, such as RMSEA = 0.071, TLI = 0.958, CFI = 0.966, and SRMR = 0.031. All of these values are considered acceptable based on the standards Hair et al. [78] proposed for model acceptance. This indicates that the observed data and the predicted model have a good fit.

TABLE 2. Industry distribution.

Industry	Frequency	%
Manufacture of food products	117	10.97
Manufacture of other machinery and equipment	117	10.97
Manufacture of fabricated metal products, except machinery and furniture	89	8.34
Manufacture of electrical equipment	78	7.31
Manufacture of electronic components, computers, visual, sounding, and communication equipment	77	7.22
Manufacture of rubber and plastics products	67	6.28
Manufacture of medical, precision, and optical instruments, watches, and clocks	61	5.72
Manufacture of motor vehicles, trailers, and semitrailers	58	5.44
Manufacture of chemicals and chemical products, except pharmaceuticals and medicinal chemicals	50	4.69
Manufacture of other transport equipment	50	4.69
Manufacture of wearing apparel, clothing accessories, and fur articles	45	4.22
Manufacture of basic metals	42	3.94
Manufacture of leather, luggage, and footwear	35	3.28
Manufacture of other non-metallic mineral products	35	3.28
Manufacture of textiles, except apparel	34	3.19
Manufacture of pulp, paper, and paper products	27	2.53
Manufacture of furniture	22	2.06
Other manufacturing	18	1.69
Printing and reproduction of recorded media	18	1.69
Manufacture of wood and products of wood and cork, except furniture	12	1.12
Manufacture of beverages	7	0.66
Manufacture of pharmaceuticals, medicinal chemicals, and botanical products	6	0.56
Manufacture of coke, briquettes, and refined petroleum products	2	0.19

Table 4 shows the standardized factor loading, Cronbach's alpha, composite reliability (CR), and the average variance

TABLE 3. Research variables and measures.

Variable	Item description	Reference
Top Management Support (TMS)	Top management's interest and willingness to support information systems Top management's active investment and strategic planning for information systems	[37], [39], [49], [73], [74]
Expected Benefits of Smart Production System (EBSPS)	Increased production Reduced costs Reduced defects Strengthened production customization Reduced process time	[35], [75]
Performance of Existing Production Systems (PEPS)	Reduced lead time Less effort to complete tasks Improved accuracy Accelerated decision-making Increased level of information sharing and cooperation across the firm Increased level of information sharing and cooperation among firms	[37], [49], [58]
Intention of Smart Factory Transformation (ISFT)	Intention of adopting and introducing a smart factory	[17], [41], [76]

TABLE 4. Reliability and validity.

Construct	Measure	Standardized factor loading	Cronbach's α	CR	AVE
TMS	TMS1	0.855***	0.884	0.898	0.821
	TMS2	0.954***			
EBSPS	EPSPS1	0.895***	0.908	0.927	0.718
	EPSPS2	0.892***			
	EPSPS3	0.854***			
	EPSPS4	0.795***			
	EPSPS5	0.795***			
PEPS	PEPS1	0.845***	0.908	0.916	0.649
	PEPS2	0.857***			
	PEPS3	0.835***			
	PEPS4	0.759***			
	PEPS5	0.797***			
	PEPS6	0.731***			
ISFT	Single measure				

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

extracted (AVE) of all measures. Clearly, the standardized factor loading of all measures exceeded 0.500, and the corresponding t-values were statistically significant at the 5% significance level. These results support the convergent validity of the measures [79]. The internal consistency of the

TABLE 5. Correlation analysis.

Construct	AVE	SQRT (AVE)	TMS	EPSPB	PEPS
TMS	0.821	0.906	1.000		
EBSPS	0.718	0.847	0.040	1.000	
PEPS	0.649	0.806	0.334	0.290	1.000
ISFT	1.000	1.000	Single measure		

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; SQRT(AVE): Square root of AVE

TABLE 6. SEM results.

Hypothesis	Unstandardized coefficient	Standardized coefficient	SE	CR	p-value	Results
H1. TMS → EBSPS	-0.098	-0.054	0.054	-1.797	0.072	Not supported
H2. TMS → PEPS	0.277	0.335	0.030	9.140	***	supported
H3. PEPS → EBSPS	0.599	0.310	0.068	8.752	***	supported
H4. EBSPS → ISFT	0.229	0.287	0.031	7.453	***	supported
H5. PEPS → ISFT	0.196	0.127	0.060	3.284	**	supported
Fit indices	Chi-square = 433.240 (d.f = 73, p < 0.001) RMSEA = 0.068 TLI = 0.955 CFI = 0.964 SRMR = 0.035					

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

measures was validated using Cronbach's alpha and CR, and both were greater than 0.7 for all measures [80], [81]. Furthermore, the AVE of TMS, EBSPS, and PEPS exceeded the recommended level of 0.5 [82], thus confirming the convergent validity of the measures.

The discriminant validity should be examined to verify that the conceptual constructs are sufficiently independent [83]. Therefore, it was verified whether the squared root of AVE exceeds the correlation coefficient between the latent constructs. Table 5 presents the correlation matrix for all the variables. As seen in the table, all the squared roots of AVE are larger than the correlation between constructs, thus indicating a high discriminant validity [82]. These findings suggest the existence of a high convergent and discriminant validity in the research model.

B. STRUCTURAL MODEL AND HYPOTHESES TESTING

A structural equation modeling (SEM) was conducted using AMOS 22.0 to empirically validate the model in Fig. 1. Table 6 presents the results of this analysis. The model was found to be a good fit: χ^2 value = 433.240, d.f. = 73, p-value < 0.001, RMSEA = 0.068, TLI = 0.955, CFI = 0.964, and SRMR = 0.033. Hypothesis 1 is found to be statistically insignificant at the 5% significance level, indicating that no statistically significant relationship exists between top

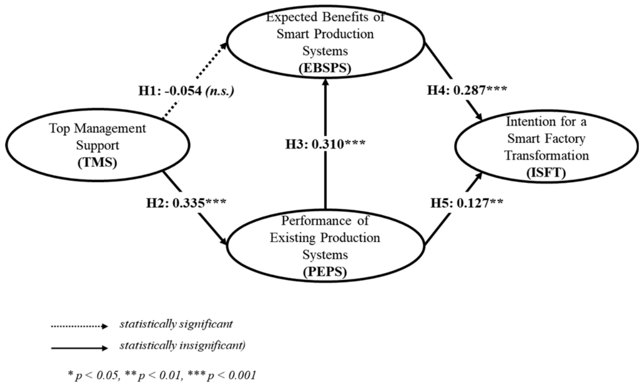

FIGURE 2. Results of structural equation modeling and hypotheses testing.

TABLE 7. Direct, indirect, and total effect of PEPS on ISFT.

Relationships	Direct effect	Indirect effect	95% CI	Total effect	95% CI
PEPS → EBSPS	0.599**			0.599**	[0.446, 0.731]
EBSPS → ISFT	0.229**			0.229**	[0.169, 0.289]
PEPS → ISFT	0.196**	0.137**	[0.094, 0.192]	0.333**	[0.217, 0.449]

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

management support and the expected benefits of smart production systems. However, Hypotheses 2–5 are statistically validated at the 0.1% significance level. The direction of their coefficients indicates the existence of positive relationships.

Fig. 2 illustrates the results of SEM and testing the hypotheses. The values in the arrows denote the standardized coefficient of the path. Table 5 and Fig. 2 confirm that the top management's support significantly and positively affects the performance of the existing production systems (H2), but it insignificantly affects the expected benefits of smart production systems. It is also verified that the performance of the existing production systems positively affects the expected benefits of smart production systems (H3) and SMEs' intention to transform (H5). Finally, the expected benefits of smart production systems increase the likelihood of their intention to adopt a smart factory (H4). With H4 and H5 validated, the performance of the existing production systems has a simultaneous direct and indirect effect on the intention to adopt a smart factory. As can be seen in Table 7, the direct and indirect effect of PEPS on ISFT are both statistically significant at the 5% significance level. The coefficient of the direct effect is 0.196 and that of the indirect effect is 0.137.

C. MULTIGROUP ANALYSIS

A multigroup analysis was performed across two groups to determine whether the mechanism of introducing smart factories differs in the two groups based on outsourcing experiences. Two groups were defined for this analysis: the in-house development experience group and the outsourced development experience group. Firms in the former group developed and implemented their information systems by themselves, whereas those in the latter group outsourced the implementation of information systems either fully or partially.

TABLE 8. Results of testing metric invariance.

Chi-square	d.f.	P-value	CFI	RMSEA	TLI
(Unconstrained Model)					
583.672	144	0.000	0.957	0.054	0.945
(Constrained model*)					
600.077	154	0.000	0.956	0.052	0.948
(Comparison test)					
16.405	10	Result: insignificant			

* Constrained in measurement weights

TABLE 9. Results of multigroup analysis.

Chi-square	d.f.	P-value	CFI	RMSEA	TLI
(Unconstrained model)					
606.870	146	0.000	0.955	0.054	0.944
(Constrained model*)					
639.383	161	0.000	0.953	0.053	0.947
(Comparison test)					
32.513	15	Result: significant			

* Constrained in measurement weights and structural path

To test metric invariance, it was examined whether each indicator contributed to the conceptual construct to a similar degree across groups. The chi-square difference test was performed using the confirmatory factory analysis model to check whether the difference between the unconstrained and constrained models is statistically significant. In the unconstrained model, no restrictions were imposed on the equality of the measurement weights. Meanwhile, the constrained model was restricted by the condition that no difference exists in any measurement weight (factor loadings of the construct's measures) between the two groups. Table 8 shows the results of testing metric invariance. Evidently, the null hypothesis that the two models have no difference is not rejected at the 5% significance level, confirming metric invariance in the multigroup analysis.

After metric invariance was confirmed, a multigroup analysis was conducted to test Hypothesis 6. The unconstrained model was estimated without restricting the equalities of structural paths. Then, the equality constraint was applied to every structural path and measurement weight to create a constrained model. Table 9 presents the results of the multigroup analysis. The differences between the chi-square values in the two models is statistically significant at the 5% significance level, indicating that the mechanism of introducing smart factories varies depending on the firm's outsourcing experiences. In other words, the degree of influence exerted by the determinants of smart factories' adoption differs based on whether the firm implemented the existing information systems through outsourcing.

A pairwise post-hoc comparison test revealed that two structural paths are significantly different across the two groups. The first difference was observed in TMS → PEPS at the 5% significance level, indicating that the effect of top management support for information and production systems on the performance of the existing production systems differs based on whether the firm outsourced its existing information systems. Furthermore, the effect of top management support was stronger in the in-house development experience group than in the outsourced development experience group. The standardized coefficient of the former group was 0.426, whereas that of the latter group was 0.290. The second difference was observed in EBSPS → ISFT at the 5% significance level, indicating that the effect of smart factories' expected performance on their adoption differs based on whether the firm outsourced its existing information systems. The standardized coefficient of the in-house development experience group was 0.465, whereas that of the outsourced development experience group was 0.181. The effect of EBSPS on ISFT seems to reduce for those firms who had outsourced their existing information systems. No significant difference was observed at the 5% significance level in the other paths across the two groups.

V. DISCUSSION

The findings and their implications are summarized as follows. First, the performance of the current production systems enhances the expected benefits of the smart production system, which in turn, increases firms' intentions to adopt smart factories. In other words, firms' experience with their existing information systems elevated their expectations from the smart production system, thus amplifying their intention of adopting a smart factory. A smart factory innovates production and manufacturing by applying advanced information technologies [17], and it is starkly different from traditional information technologies and operations systems, such as ERP, MES, PLM, and SCM. However, these traditional technologies and systems are crucial for the successful adoption of smart factories [17]. Thus, smart factories must be developed based on these existing production systems. From a managerial perspective, practitioners can strategically develop a favorable opinion toward technology-driven production systems such as smart factories using the results of this study. If the current production systems increase workforce productivity and benefit employees, firms may expect that a smart production system will benefit them highly and initiate their implementation. Expectations of high benefits and strong intentions of implementing smart factories can positively influence stakeholders who oppose the innovation, thinking that it is disruptive. Before developing a smart factory, practitioners should prioritize evaluating and enhancing the performance of the current production systems.

Second, even if the top management supports information and production systems, their support does not increase the benefits expected from smart production systems. However, their support can be used to improve the performance of the current production systems, which can be used to increase the perceived usefulness of smart factories and accelerate their adoption. Therefore, even if the top management intends to support technology-driven production systems and develop a smart factory, there may not be a positive opinion about it if the firm's current production systems do not operate efficiently. Thus, top managers must assess the effectiveness of the current production systems before deciding on whether to develop a smart factory.

In addition, the top management should consider ways to increase employees' expectations from smart factory transformation. Building this expectation will require the skillful management of employees' resistance to the adoption of new technologies [84] and unfavorable perceptions that they are being replaced [85].

Finally, the determinants of the adoption of smart factories can be utilized more effectively if firms develop their production systems internally. The effect of top management support on the performance of the current production systems and the effect of smart factories' perceived usefulness on their adoption is greater when firms develop their production systems in-house. In many cases, outsourcing the establishment of information and production systems introduces challenges [25]. There may be communication and coordination issues due to the complexity of companies' collaborative networks. The development of a smart factory may be outsourced if the firm has limited experience in developing and managing their existing production systems. Employees may anticipate similar issues that they had faced while implementing the existing systems or a significant amount of work in developing a smart factory. In this case, even if the existing production systems operate successfully, the perceived usefulness of smart factories and the willingness to adopt them may be lower than if the firm had developed their existing systems in-house. Consequently, additional efforts will be required to increase the willingness of adopting smart factories in firms that frequently use the outsourced development approach. Thus, companies should carefully consider which approach is more beneficial in developing smart factories: in-house or outsourced development [86].

Overall, firms are likely to make decisions in partaking smart factory transformation based on the successes of other companies. Aligned with the global management trend in encouraging the adoption of smart factories through non-profit, social, and government activities (i.e., the European Commission-funded initiative WATIFY, the Make in India initiative, and the Build 30000 Smart Factories in Korea initiative) [15], [30], [32], this study provides practical solutions to accelerate the rate of smart factory adoption. To encourage the transition to smart factories, successful transformation cases are imperative. In that regard, this study offers a suggestion for promptly gathering and analyzing successful smart factory transformation cases of manufacturing SMEs. Thus, the adoption rate of smart factories will accelerate rapidly if these firms are first encouraged to develop them.

VI. CONCLUSION

The interest in Industry 4.0 and smart factories is accelerating globally. Aligned with this trend, this study empirically analyzed the mechanism of the adoption of smart factories and identified the factors influencing their adoption in Korean manufacturing SMEs. In addition, it assessed the moderating role of in-house and outsourcing experiences on the overall mechanism. This study significantly contributes to the literature because it empirically examines the overall process of introducing smart factories, in contrast to previous studies, which were often conducted using conceptual analyses or case studies. In addition, this study provides empirical evidence supporting the statement that current production systems will serve as the foundation for smart factory transformation [2], [3], [23], [57].

The findings of this study offer practical recommendations for companies compelling to invest in new, technology-driven manufacturing systems, helping establish appropriate strategies for smart factory transformation. Firms may foster a favorable opinion toward smart factory systems by enhancing the performance of the current production systems and by increasing the top management's intention to support. Additionally, this study provides policymakers with a valuable suggestion on how to accelerate the transformation of conventional factories into smart factories. Companies that commonly utilize outsourcing-based development strategies will need to make further efforts to increase their willingness to adopt smart factories. Thus, companies with less outsourcing experience should be encouraged first to convert into smart factories.

Despite its utility, this study has the following limitations. First, the sample consisted of only small and medium-sized enterprises. As shown in Table 1, only 1.59% of the companies had annual sales of USD 500 million or higher. Generally, SMEs have limited resources that can be utilized for developing a smart factory [58]. On the contrary, large firms have ample resources and can plan new changes more systematically and even benefit from outsourcing tasks. Furthermore, large companies and small and medium-sized enterprises differ in terms of their application of information and production systems, the scope of their systems, and productivity. Therefore, it is possible that large companies and SMEs introduce smart factories using different mechanisms. Future studies should include large companies in exploring the mechanism of the adoption of smart factories. Such studies may present more comprehensive results because researchers will be able to investigate the significance of variances based on the firm's size.

Second, this study analyzed companies dispersed across 23 manufacturing industries, but SMEs possess different characteristics depending on their industry. The degree to which information technology is utilized in a firm, the type of information and production systems it employs, and its needs for adopting a smart factory may differ based on the industry it operates in. Therefore, future studies must categorize industries based on the related sectors to conduct an in-depth analysis on smart factory transformation process and the difference between industries.

Finally, even if the top management strongly intends to pursue smart factory transformation, employees' resistance can make it challenging for the top management to make any progress [84]. This problem may worsen if there are many senior employees who are unable to adopt technological advancements or strongly oppose adopting new systems owing to the fear of being replaced by new technologies [87]. More implications might be drawn by including employees' feelings in the research model of future studies.

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