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KEY SUCCESS FACTORS OF BUSINESS PERFORMANCE: EVIDENCE FROM SMART FACTORIES IN SOUTH KOREA

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ABSTRACT

The purpose of this study is to reveal the effects of key smart-factory success factors—the Internet of Things (IoT), big data, artificial intelligence (AI), fifth-generation (5G), and MES (manufacturing execution systems)—on the continuous use and business performance of smart factories in small and medium-sized manufacturing companies. To achieve this, an empirical survey was conducted with 189 key managers in 50 small and medium-sized enterprises (SMEs) that have established smart factories with government aid, and the responses were analyzed with a structural equation model using the AMOS program. The research findings show that these success factors were only partially effective—they had a positive effect on the continuous use of smart factories by SMEs, as well as the factories' productivity and quality performance (sub-factors of business performance), but had no significant effect on financial performance. This means that the effective utilization of these factors can enable high-quality performance by maintaining operational efficiency. Consequently, the integration and utilization of IoT, big data, AI, 5G, and MES based on AI technologies have policy and practical implications, showing that they should be used as key success factors in SMEs.

Keywords: *Smart Factory, Key Success Factors, Business Performance, Korea, Small and Medium Enterprises*

1. INTRODUCTION

Various reports and media publications that predict future changes in jobs are now mentioning smart factories, which are expected to have a significant impact on the manufacturing industry [1]. Smart factories are key to implementing unmanned production processes as they store all the related information and connect equipment, machines, materials, and parts comprising the manufacturing process, in addition to providing intelligent information based on the stored information. This means that a smart factory can minimize production

Recently, the manufacturing and consumption environment has been changing rapidly with the development of information and communications technology (ICT). Moreover, to revive the economy by enhancing the manufacturing industry's competitiveness in the context of the global Fourth Industrial Revolution, governments

labor, as all production processes are integrated with intelligent information under the existing economic system of low-variety mass production, as well as strengthen the manufacturing industry's competitiveness through customized small-quantity batch production focused on individuals' needs. Based on this trend, the major manufacturing powerhouses of Germany, the United States, and Japan are devoting efforts to implementing a smart manufacturing industry with the vision of sophisticated, open, and feasible smartification [1].

are pursuing related policies and concentrating on economic and technical support by mobilizing all capabilities at the national level. The smart factory is an example of this [2].

Smart factories have assumed great significance in South Korea in the past three to four years; following a survey of domestic small and

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medium enterprises (SMEs), the Ministry of SMEs and Startups reported that 68% of companies are considering the introduction of a smart factory [3]. Although this explains why various media have mentioned the Fourth Industrial Revolution and are treating smart factory as a key issue, most companies only have a vague understanding of these two topics [3]. However, one can infer that this is due to the realistic anxiety that "[firms] feel the need to prepare to survive through competition, and it is impossible to know the specific direction for corporate survival due to the current economic situation" [3].

On March 8, 2018, the South Korean government announced the Smart Factory Proliferation and Advancement Strategy with the aim of supplying 20,000 smart factories by 2022 as part of the projects leading innovation growth. The government is pushing for the conversion of these 20,000 companies (about one-third of the 67,000 manufacturing SMEs with more than 10 employees) into smart factories by further strengthening promotional policies [4].

The government has already supported and supplied smart factories to 5,003 SMEs between 2014 and 2017. An analysis of the performance of companies in which smart factories have been deployed shows that they experienced a 30% increase in productivity, 45% decrease in defect rate, 15% reduction in cost, and employment creation of an average of 2.2 employees per company [4]. Despite the improvement in performance, many participating companies experienced high anxiety since they were not sure how to apply and adopt factors from the perspective of demand companies to build a smart factory, and only 50% were satisfied with the coaching provided by experts from the smart factory promotion group. This indicates that, in the absence of international standards, there is great concern about the current investment becoming a sunk cost if it has no future scalability [5]. Especially, there is anxiety about the key successes and low trust in performance improvement through continuous investment due to a lack of information on supply companies as well as distrust in their technological level. This is an obstacle to the introduction of smart factories in the small and medium-sized manufacturing industry [6].

Accordingly, this study seeks to derive industrial and interdisciplinary implications by reviewing the theoretical background of previous studies in section 2. Through research model establishment and hypothesis verification, section 3 reveals the effects of key success factors of effective smart factories on their continuous use and business performance. In section 4, the structural model is applied to derive key success factors that could affect the business performance of the smart factory and to verify the mediating effects.

2. THEORETICAL BACKGROUND

2.1 Key Success Factors of Smart Factories

The smart factory applies various forms of ICT to manufacturing by integrating human skills, technology, and information to bring about strategic innovation in the manufacturing industry [7]. It connects, integrates, and autonomously operates equipment, factory management, human resources, and the supply chain network based on the operation, information, and data technologies [8].

The smart factory is unique in that it can form its own best judgments based on the information collected in various ways and places, which is unlike factory automation that simply replaces human labor [9]. It is a single factory system in which all components of the factory manufacturing value chain achieve vertical and horizontal integration, communication, and collaboration in real time. As such, the factor differentiating it from the existing factory automation is the implementation of automation and digitization through integration with the Internet of things (IoT), artificial intelligence (AI), and big data [10, 11].

The implementation of smart factory has made it possible to not only correlate all the problems that occur at production sites, based on the vast amounts of data collected at each factory, but also facilitates optimal decision-making through the collection of information in real time. Most smart factories have not yet reached the advanced stage of implementing AI systems that perform autonomous judgments. Instead, they focus on increasing the efficiency and stability of equipment, improving productivity, reducing costs through remote management, among other things, as well as predicting and determining the operation status and failure of machines and the possibility of product defects [9]. The ultimate goal of a smart factory is to operate a manufacturing company that can enhance productivity and reduce production costs through an intelligent, flexible, optimized, and efficient production system, as well as actively respond to the rapidly changing external environment and customer needs [12].

The key success factors of a smart factory include the application layer of demand-customized process, operation optimization technology, prediction-based quality, and facility advancement technology; the platform layer of big data analysis and cyber physical systems (CPS); and the device/network layer of cognitive smart sensor technology. These technologies are recognized as success factors [2].

The smart factory is a production system in which the factory equipment and device components are connected and communicate with each other through technologies such as IoT, big data, cloud computing, and CPS, by combining ICT and the existing production manufacturing technology [13]. Moreover, all the data in the production process are collected and used to construct intelligent systems through AI technologies such as IoT, big data, and deep learning, as well as ICTs such as robotic and equipment automation. To enable flexible production, the smart factory seeks activeness, agility, and reliable production. Based on these theoretical criteria, this study aims to reflect on these factors and determine the relationship between the key success factors of the smart factory and their effects on continuous use in SMEs through an empirical survey.

2.2 Relationship between Smart Factories and Continuous Use

"Continuous use" refers to the willingness of users who, following the introduction of a smart factory, have used the information system at least once and continue using it. In the smart factory, continuous use has been utilized as a system's operation to assess the true success of products or services. Thus, while research on the users' intention to accept an information system is important, the definition of continuous use intention is also vital for the expansion of corporate profits [14].

By making strategic decisions, chief executives can control the key issues inside and outside the organization and influence the entire organization, including aspects such as the formation of organizational culture and the design of the organizational structure [15].

The rational behavior theory explains that users' intention to build the smart factory system is influenced by the technology acceptance model (TAM) based on the relationship between belief, attitude, intention, and behavior [16]. When new products provide customers with the value that previous products could not deliver in terms of performance or functionality, the establishment of a new system is rapidly accepted in the market [17]. The newly perceived usefulness here is related to the users' subjective beliefs about how useful a certain adopted technology will be relative to their business productivity and efficiency. Thus, the use of certain technology can be understood by evaluating the corresponding improvement in productivity performance [18].

Rogers [17] argued that the quicker users learn how to use a product, the faster the new product will be accepted in the market. Perceived usefulness has been shown to directly impact the intention of continuity. Kim [19] analyzed the effects of variables—cost, reliability, security, functionality, and accessibility—on technology acceptance performance through the mediation of perceived usefulness and perceived continuity using the TAM [20]. He found that there was a positive relationship between perceived usefulness, perceived continuity, and information technology use performance in TAM [16, 21, 22].

Perceived usefulness and continuity have a subjective correlation with the establishment of smart factories. The more positive the relationship between these two is, the more positive the effect they have on the continuous use of smart factories. The more users feel that smart factories are useful, the more they will continuously use such factories; however, despite their advantages, if the use of smart factories involves complications or difficulties that are not quickly resolved, users will tend to avoid them.

2.3 Relationship between Smart Factory Introduction and Business Performance

The smart factory obtains all the information about manufacturing facilities in real time through the Internet, changes manufacturing methods autonomously, replaces raw materials and ultimately implements the optimized dynamic production system [23]. A smart factory uses ICTs such as process automation, factory automation, factory energy management, product development, and collaborative information management systems of supply chain management and enterprise resource planning based on facility and logistics automation [24, 25]. This means that the smart factory implements vertical integration based on the factory's production equipment system and horizontal integration based on the product development value chain, starting with the implementation of the customers' requirements [26]. Horizontal integration of the value chain involves market research and product planning to derive the requirements of customers who use the products, product development, and process design to meet customer requirements, and, subsequently, production and delivery to the customer [27]. Beyond factory automation, it implements the automation of production systems that occur within manufacturing plants, such as product design planning, maintenance, and quality control. In other words, future factories that produce customized products with minimum cost and time will utilize the core technology of IoT to integrate the entire process of product planning, design, production, distribution, and sales into ICT and CPS. Thereby, all stages of

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manufacturing are automated, and the entire value chain operates as a factory-like production system with real-time interactions [2, 28].

Chiang and Lee [29] stated that smart manufacturing uses sensors and analyzes data to improve the production efficiency of factories. Park [23] argued that the integration of production systems, product life cycles, and intercompany value chains are the critical success factors of smart factories that can improve productivity. In addition, David et al. [30] claimed that smart factories had a positive effect on the provision of a variety of benefits such as improved process efficiency, product quality, sustainability, safety, and cost savings.

Based on the positive effects of smart factories, the South Korean government is promoting the domestic introduction of the smart factory through various policies. According to a recent press release by the Ministry of SMEs and Startups, about 7,800 companies supported the introduction of the smart factory; about 4,430 companies built smart factories in 2018; and, 570 companies are in the process of building smart factories [31]. Moreover, 80% of companies that promoted smart factories since the beginning as a pilot project in 2014 responded that they had increased their driving force and productivity by 30.0%, decreased their defect rate by 43.5%, reduced costs by 15.9%, improved delivery date compliance by 15.5%, and reduced industrial accidents by 22%. This was achieved by collecting basic data about internal production equipment, logistics, and production information using ICT—this improved productivity led to increased sales [31].

As such, a smart factory refers to an evolved factory that produces customized products with minimal cost and time by integrating the entire process of planning, design, production, distribution, and sales through ICT. It is a key success factor that differentiates itself from existing factory automation by implementing process automation and digitalization through the integration of IoT, AI, and big data. In the past, factory automation was established for mass production, but as one factory accepts the change, there is unity in the operation of every factory, and more will adopt. In the planning and design stages, the simulation of product performance in the virtual space before manufacturing can shorten the manufacturing period for products customized to consumer needs. In the production stage, the real-time information exchange between the equipment-material-management systems can support the production of various products in the same factory, improving the efficiency of energy and facility. In the distribution and sales stages, real-time automatic orders in line with production conditions can substantially reduce the inventory cost, maximizing performance through cooperation in all fields, including quality and logistical performance [32].

Consequently, based on this mutual causality, this study also conducts an empirical analysis reflecting these variables to identify the effects of the key success factors of smart factories on continuous use and business performance in manufacturing SMEs.

3. STUDY DESIGN

3.1 Research Model

Currently, when key technologies of the Fourth Industrial Revolution and fifth-generation mobile networks (5G) are being applied and commercialized increasingly in industrial sites and everyday life in the globalized world, companies are facing infinite global competition. Thus, they are looking for ways to reflect the diverse needs of customers and "build a new manufacturing/service paradigm that can respond to changes" with corporate management policies to survive while facing competition [28]. While smart factories are being discussed as an alternative to overcome this reality effectively, domestic industrial policies, which have been biased toward quantitative growth, have not responded flexibly to the qualitative growth and changes that introduce core smart factory technologies [20, 25].

Depending on manufacturing characteristics and circumstances, the key technologies of smart factories are converging with other technologies and methods. They are being implemented as a factory system through the inter-process convergence of vertical and horizontal functions for the innovation of manufacturing processes in factories [9, 12]. South Korea ranks fifth in global manufacturing and first in the information technology development index. However, compared to other countries, South Korea's development level of key technologies for smart-factory operation is 70%–80%, as its product lifecycle management and computer-aided design are mostly dependent on foreign companies [23, 29]. Significant human resources, research and development, and investment of funds must precede the introduction of the key factor technologies of smart factories to build the manufacturing and service system. However, SMEs lacking in capital financing and human resources have many difficulties in pursuing technological solutions to find, develop, and research technologies to overcome challenges and achieve the future vision.

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Accordingly, this study aims to examine the effects of IoT, big data, AI, manufacturing execution system (MES), and 5G as the key success factors of smart factories on continuous use and business performance, including production performance and quality performance. In this respect, the research model presented in Figure 1 is established to empirically reveal the intrinsic variables and their influencing factors through quantitative measurements.

[Figure 1 near here]

3.2 Hypothesis Formulation

Based on the research model, the following hypotheses were formulated to reveal the effects of key technology factors of smart factories on continuous use and business performance.

Hypothesis 1. Key success factors of smart factories affect continuous use in manufacturing SMEs.

Hypothesis 2. Key success factors of smart factories affect quality performance in manufacturing SMEs.

Hypothesis 3. Key success factors of smart factories affect production performance in manufacturing SMEs.

Hypothesis 4. Continuous use plays a mediating role in the effect of the key success factors of smart factories on quality performance in manufacturing SMEs.

Hypothesis 5. Continuous use plays a mediating role in the effect of the key success factors of smart factories on production performance in manufacturing SMEs.

3.3 Data Collection

3.3.1 Questionnaire composition

The questionnaire used in this study included the IoT, big data, AI, 5G, and MES as independent variables by applying the convergence technology factors of the Fourth Industrial Revolution, in line with Jang et al. [8] and Jang [9], as key success factors after the establishment of smart factories. Moreover, production performance and quality performance are also measured, as they are factors affecting corporate business performance through continuous use, based on Rogers's [17] TAM theory and Kim's [19] study.

To determine the data characteristics from among a total of 48 items, the questionnaire comprised 6 items on a nominal scale and 42 items on a 5-point Likert scale, focusing on production performance and quality performance as the success factors and the sub-factors of business performance after the establishment of smart factories.

3.3.2 Data collection

The purpose of this study is to examine the effects of the application level of core technologies on the business performance and continuity of companies that have introduced smart factories, as well as to develop improvement plans through an execution guideline to promote smart factories. The 150 companies that had promoted smart factories with the support of the South Korean government and 50 SMEs that had promoted smart factories with their plans were selected for accuracy of data collection from the population. Among a total of 200 questionnaires, 189 were collected and used for analysis.

The distribution of the collected data is shown in Table 1.

Table 1: Descriptive Statistics

Classification	N	Mean	Standard Deviation	Minimum	Maximum
IoT	189	3.17	0.76	1	5
Big data	189	3.13	0.69	1	5
AI	189	3.16	0.71	1.25	5
5G	189	3.15	0.78	1.25	5
MES	189	3.04	0.71	1	5
Continuous Use	189	2.84	0.94	1	5
Production Performance	189	2.89	0.91	1	5
Quality Performance	189	2.82	0.74	1	4.625

Note: IoT = Internet of things; AI = artificial intelligence; 5G = fifth-generation mobile networks; MES = manufacturing execution system.

3.4 Analysis Method

In this study, the SPSS.25 and AMOS programs were used for statistical processing. Through empirical analysis of the survey data, the frequency and percentage were calculated to identify the characteristics of the companies. Reliability and exploratory factor analysis were conducted to identify the validity and reliability of the survey tool. Confirmatory factor analysis of the measurement model was conducted to determine whether the survey tool's overall validity is supported through the AMOS program. Finally, path analysis was

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conducted to identify the relationship between the variables, and a bootstrapping test was conducted to verify the mediating effect.

The survey was administered to 200 subjects, and 189 responses were used for the analysis (11 were excluded, as they had many missing values); hence, the recovery rate was 94.5%.

3.5 Frequency Analysis

Table 2 below shows the types of companies that responded to the survey and the characteristics of the respondents.

Table 2: Results of Frequency Analysis

Category	Frequency	%	
Sector	Electricity and electronics	24	12.7
	Chemical manufacturing	31	16.4
	Textile manufacturing	25	13.2
	Pharmaceutical and medical manufacturing	13	6.9
	Casting heat treatment manufacturing	25	13.2
	Machinery and parts manufacturing	42	22.2
	Mold processing manufacturing	15	7.9
	Other	14	7.4
Number of employees	10 employees or less	6	3.2
	11–50 employees	46	24.3
	51–100 employees	34	18
	101–200 employees	58	30.7
	201 employees or more	45	23.8
Sales	5 billion won or less	43	22.8
	5.1–7 billion won	52	27.5
	7.1–12 billion won	47	24.9
	12.1–20 billion won	27	14.3
	20.1 billion won or more	20	10.6
Time since smart factory introduction	Less than 6 months	24	12.7
	6 months–1 year	77	40.7
	1–2 years	32	16.9
	2–3 years	46	24.3
	3 years or more	10	5.3
Purpose of smart factory introduction	Cost reduction flexible response	7	3.7
	Secure competitiveness by changing manufacturing environment	18	9.5
	Labor cost reduction	29	15.3
	Government support and policy	18	9.5
	Learning through broadcast and media	43	22.8
	Internal staff agreement	63	33.3
	Recommendation from others	11	5.8

4. ANALYTICAL RESULTS

4.1 Reliability and Validity Analysis

The validity and reliability verification results for the variables are shown in Table 3. Based on the reliability analysis, Cronbach's alpha was at least 0.7 in all variables, thus satisfying the reliability requirements, and the K-M-O was 0.7 or more, thus confirming the validity. As such, they were used in the analysis without modification.

Table 3: Reliability Analysis and Exploratory Factor Analysis Results

Category		Number of items	Cronbach's alpha	K-M-O test
Key success factor	IoT	4	0.804	0.749
	Big data	4	0.727	0.715
	AI	4	0.762	0.746
	5G	4	0.834	0.778
	MES	4	0.813	0.778
Continuous use		4	0.930	0.855
Business performance	Productivity	10	0.839	0.816
	Quality performance	8	0.858	0.859

Note: K-M-O = Kaiser-Meyer-Olkin; IoT = Internet of things; AI = artificial intelligence; 5G = fifth-generation mobile networks; MES = manufacturing execution system.

4.2 Confirmatory Factor Analysis

Table 4 shows the verification results for convergent validity according to the confirmatory factor analysis of the variables. It is necessary to satisfy the standardization factor loading of 0.5 or more, T-

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value of 1.965 or more, average variance extracted of 0.5 or more, and construct reliability of 0.7 or more, to ensure the convergent validity of each variable [33, 34].

Table 4: Confirmatory Factor Analysis Results

Category		Factor loading	T-value	Construct reliability	AVE
Key success factor	IoT	0.643	8.203	0.914	0.68
	Big data	0.775	9.812		
	AI	0.78	9.877		
	5G	0.74	9.401		
	MES	0.714	fix		
Business performance	Productivity	0.902	fix	0.911	0.84
	Quality performance	0.852	16.901		

Note: AVE = average variance extracted; IoT = Internet of things; AI = artificial intelligence; 5G = fifth-generation mobile networks; MES = manufacturing execution system.

This study used all three methods to verify convergent validity. According to the convergent validity analysis of all the variables, the criteria for validity were satisfied, and the variables were thus used for analysis without modification.

4.3 Path Analysis

The fit index of the research model showed that chi-square = 103.893, degrees of freedom = 18, goodness of fit index (GFI) = 0.957, adjusted goodness of fit index = 0.906, comparative fit index (CFI) = 0.979, and root mean square residual (RMR) = 0.021. As the GFI and CFI were at least 0.9, and RMR was less than 0.05, the model was deemed fit. Therefore, the structural equation model for these hypotheses was confirmed to have good overall fit, and the fit of the path coefficient was also verified.

The adoption or rejection of each hypothesis and the results of the path analysis are summarized in Table 5. Figure 2 illustrates the result of the structural equation modeling analysis.

[Table 5 near here]

[Figure 2 near here]

4.4 Mediating Effect

The results of the structural model bootstrap analysis were analyzed to determine whether continuous use plays a mediating role in the effect of the key success factors on the business performance of manufacturing SMEs. In the process of verifying the mediating effect hypothesis, estimable bootstrapping with abnormal data was repeated 500 times to verify the significance of the indirect effect, and the replicated sampling was measured at the significance level of .05.

Table 6 shows the results of analyzing the mediating effects of “Continuous use” on the impact of smart factory key success factors on “Business performance.”

[Table 6 near here]

4.5 Discussion

The above test results showed that IoT, AI, and MES are key success factors for the continuous use of smart factories in manufacturing SMEs, while big data and 5G are key success factors for productivity performance, and AI and 5G are key success factors for quality performance.

All five factors, IoT, AI, MES, big data, and 5G, were expected to improve business performance by continuously using the smart factory in small and medium-sized manufacturing companies. However, the test results confirmed that only IoT, AI, and MES were key success factors in smart factories. This means that the five key success factors should be selectively introduced and applied to the smart factory, as big data and 5G have no effect on users’ intention to continue using smart factories though they have a positive relationship with factory productivity, while AI and 5G have a positive effect on quality performance.

These results indirectly support the premise that the successful introduction of smart factories has a positive effect on convergence-linked integration [9]. The introduction of smart factories requires various adjustments to map processes to consumer customization [7]. However, key performance indicators revealed that MES and POP (Point of Production) are sensitive to these needs and responses and can help resolve them quickly. They can contribute to the smart factory’s superior production performance and improvements such as timesavings, shorter manufacturing times, and fewer defects. The relative advantages of advanced technologies based on the Fourth Industrial Revolution, recently prioritized by many countries as key success factors of smart factories, will increase corporate value. Moreover, given the innovation diffusion theory of manufacturing technology systems, the establishment of IoT, big data, AI, 5G, and MES, which are key technologies of smart factories in small and medium-sized manufacturing companies, will strengthen the corporate human resource framework and competitiveness.

5. CONCLUSIONS

Overall, smart factory IoT, AI, and MES; smart factory big data and 5G; and smart factory AI and 5G had a significant effect on continuous use, productivity performance, and quality performance, respectively. Thus, not all factors were equally effective in influencing the continuous use and business performance of smart factories in manufacturing SMEs. In addition, AI and MES as key success factors of smart factories could achieve the performance of production and quality advantage with high business performance through long-term continuous use. This means that the efficient utilization of the key success factors of the smart factory could ensure advantages through long-term continuous use and high-productivity performance based on the usefulness of smart factory information technology.

In the small and medium-sized manufacturing industry, the smart factory can actively utilize ICT for production process management and product quality management through factory automation based on logistics automation. This enhances product competitiveness and helps compete with leading companies. Furthermore, this suggests the smart factory's preferential introduction in the small and medium-sized manufacturing industry based on the proven success factors.

Therefore, implementing the smart factory enables a factory operation system based on data, which analyzes and makes decisions according to the large amount of data collected at each factory, making it possible to correlate the phenomena and problems that occur at production sites. Moreover, as optimal decisions are made by reflecting not only the information generated at manufacturing sites but also the information autonomously obtained in real time, to achieve high performance in a competitive environment, adoption of smart factories in manufacturing SMEs should be recognized as an essential process, and the system should be actively introduced.

Finally, as the survey was carried out with a small number of companies in restricted and specific areas, this study had limitations in generalizing the research results. Consequently, the research methods should be extended and supplemented through a survey of national samples in the future.

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Table 5: Final Path Analysis Result

Category	Path			Non-standardized coefficient	Standardized coefficient	S.E.	T-value	P	Adoption Status
H1-1	IoT	→	Continuous use	0.203	0.172	0.101	2.008	0.045	Adoption
H1-2	Big data	→		0.047	0.036	0.126	0.374	0.708	Rejection
H1-3	AI	→		0.32	0.234	0.114	2.814	0.005	Adoption
H1-4	5G	→		0.09	0.078	0.103	0.873	0.382	Rejection
H1-5	MES	→		0.276	0.213	0.115	2.388	0.017	Adoption
H2-1	IoT	→	Quality performance	0.046	0.051	0.056	0.815	0.415	Rejection
H2-2	Big data	→		0.128	0.128	0.069	1.846	0.065	Rejection
H2-3	AI	→		0.149	0.141	0.064	2.319	0.02	Adoption
H2-4	5G	→		0.119	0.135	0.057	2.08	0.037	Adoption
H2-5	MES	→		0.043	0.043	0.065	0.667	0.505	Rejection
H3-1	IoT	→	Production performance	-0.009	-0.009	0.059	-0.162	0.872	Rejection
H3-2	Big data	→		0.159	0.129	0.072	2.203	0.028	Adoption
H3-3	AI	→		-0.038	-0.029	0.067	-0.569	0.57	Rejection
H3-4	5G	→		0.224	0.206	0.059	3.772	***	Adoption
H3-5	MES	→		0.07	0.057	0.067	1.044	0.296	Rejection

Note: S.E. = standard error; AVE = average variance extracted; IoT = Internet of things; AI = artificial intelligence; 5G = fifth-generation mobile networks; MES = manufacturing execution system.

Table 6: Result of Analyzing the Mediating Effect

Category	path					Total effect	Direct effect	Indirect effect	Adoption Status
H4-1	IoT	→	Continuous use	→	Quality performance	0.146 (p = 0.154)	0.051 (p = 0.491)	0.095 (p = 0.063)	Rejection
H4-2	Big data	→				0.147 (p = 0.166)	0.128 (p = 0.105)	0.02 (p = 0.69)	Rejection
H4-3	AI	→				0.271 (p = 0.006)	0.141 (p = 0.12)	0.13 (p = 0.011)	Adoption
H4-4	5G	→				0.178 (p = 0.05)	0.135 (p = 0.075)	0.043 (p = 0.545)	Rejection
H4-5	MES	→				0.161 (p = 0.074)	0.043 (p = 0.499)	0.118 (p = 0.04)	Adoption

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H5-1	IoT	→	Continuous use	→	Production Performance	0.113 (p = 0.198)	-0.009 (p = 0.73)	0.122 (p = 0.057)	Rejection
H5-2	Big data	→				0.154 (p = 0.07)	0.129 (p = 0.021)	0.025 (p = 0.668)	Rejection
H5-3	AI	→				0.136 (p = 0.087)	-0.029 (p = 0.565)	0.165 (p = 0.013)	Adoption
H5-4	5G	→				0.262 (p = 0.033)	0.206 (p = 0.015)	0.056 (p = 0.558)	Rejection
H5-5	MES	→				0.208 (p = 0.043)	0.057 (p = 0.413)	0.151 (p = 0.047)	Adoption

Note: IoT = Internet of things; AI = artificial intelligence; 5G = fifth-generation mobile networks; MES = manufacturing execution system.

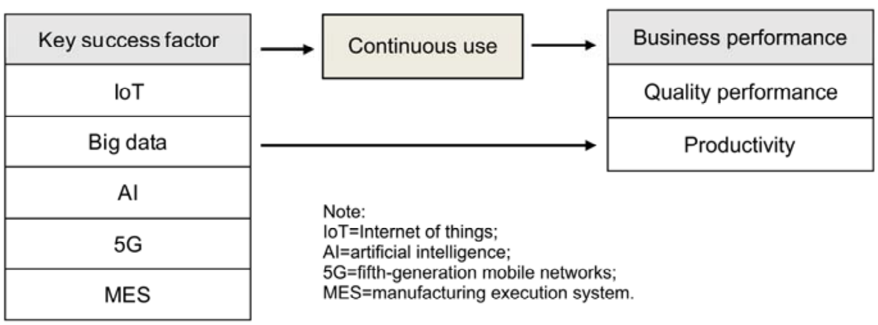

Figure 1: Research Model

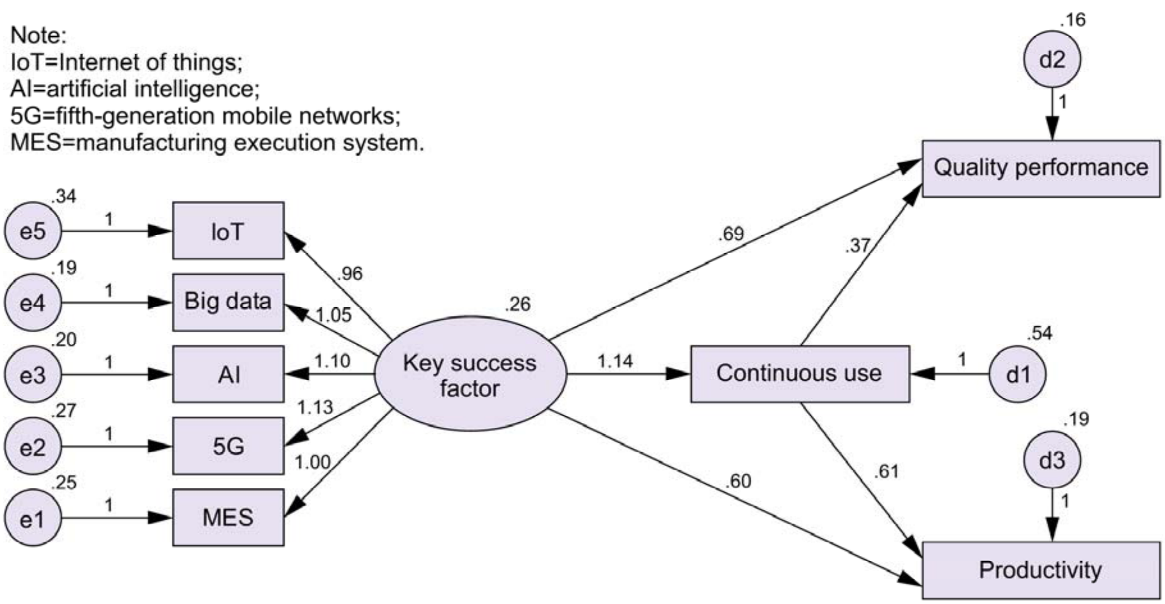

Figure 2: Final Path Model