Implementing Smart Factory: A Fuzzy-set Analysis to Uncover Successful Paths

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Abstract

Despite the pervasiveness of the Fourth Industrial Revolution, few studies have examined the adoption of smart factories. Scholars have long examined firms' willingness to adopt smart factories. Thus, this study heeds this call by investigating the factors driving the adoption of smart factories. It employs a fuzzy-set configuration approach to capture the complex interactions underlying these drivers in the context of South Korean marine equipment firms. Based on data from a sample of 180 respondents, the findings revealed four complex paths with factors including government support, the entrepreneurial spirit of top management, efficiency expectation, and financial preparedness shaping the high and low implementation of smart factories. Theoretically, the findings are an exception to extant technology acceptance models. Practically, the attention of practitioners in South Korea and other similar contexts was drawn.

Keywords: *Smart Factories*; *Government Support; Managerial Awareness; Financial Preparedness; Efficiency Expectation; fsQCA.*

1. Introduction

The concept of the Fourth Industrial Revolution was first mooted in 2011 at the Hannover Messe Trade Fair when Henning Kagermann, Wolf-Dieter Lukas, and Wolfgang Wahlster cited the incidence of 'Industry 4.0.' It has been described as the establishment of communication systems between manufacturing equipment and outputs by incorporating the Internet of Things [IoT] into the production environment to optimize processes (VDI Nachrichten, 2011). Subsequently, under the theme of 'Mastering Fourth Industrial Revolution,' the 2016 World Economic Forum raised further awareness about the advent of a new industrial shift. The notion of a 'smart factory' became an important dimension in the Fourth Industrial Revolution discourse as it pertained to manufacturing (Forschungsunion, 2013). In the aftermath of the 2008 financial crisis, leading manufacturing countries reaffirmed the importance of more efficient manufacturing, prompting the development of smart factories to optimize productivity by incorporating novel information and communication technologies (KOSTEC, 2017). Country-wise, Germany has been at the forefront of harnessing Fourth Industrial Revolution opportunities through optimized manufacturing, as has the United States, Japan, and China. To this end, various national programmes have been conceived such as the 'Advanced Manufacturing Partnership' in the United States, the 'Revised Japan Revitalization Strategy' in Japan, and 'Made in China 2025' in China. These government-led initiatives collectively intended to amplify manufacturing competitiveness by establishing smart factories.

In South Korea, a smart factory policy was launched in June 2014 when the Ministry of Trade, Industry, and Energy rolled out the Manufacturing Innovation 3.0 program. According to the Korea Smart Manufacturing Office, smart factories are intelligent facilities that enhance productivity and quality by integrating communication technologies such as the IoT, artificial intelligence [AI], and big data into a part or the entirety of the manufacturing process, encompassing planning, design, production, distribution, and sales. The objectives of Manufacturing Innovation 3.0, in South Korea, include generating added value by fusing the IT and software industries to advance the competitive advantage of the country's manufacturing. From the outset, a cluster of new manufacturing industries, mainly comprising small- and medium-sized factories, was created (Ministry of Trade, Industry, and Energy, 2014). In June 2019, the South Korean government launched a Manufacturing Renaissance Vision with the ambition of being among the top four major manufacturing nations. Specifically, this complementary strategy aimed to smarten and address the environmental sustainability of converged industrial structures. The government also announced plans to promote industrial intelligence systems that fully incorporate AI not only in smart factories and industrial complexes but also in the wider manufacturing sector (MOTIE, 2019).

In addition to these initiatives, the South Korean government has spearheaded cooperation between large companies and research institutes, particularly in the electrical, electronic, and automobile industries. However, the aggregate value of this intervention is limited because investment in smart factories in the shipbuilding and marine equipment industries remains inadequate. Accordingly, research in this area has been curtailed, although the shipbuilding and marine equipment industries in South Korea are world-leading in terms of competitiveness. In addition, as marine equipment manufacturers are ancillary to the shipbuilding industry, they depend on market trends that affect the latter (KOTRA, 2017). Since the 2008 financial crisis, falling vessel prices have meant that localizing the manufacturing of marine equipment is a path towards improving the competitiveness of the domestic shipbuilding industry (Jung, 2019). Acknowledging recent environmental regulations enacted by the International Maritime Organization (IMO) of the United Nations, the demand for eco-friendly vessels and related marine equipment is expected to increase (MOTIE, 2018). Hence, securing the competitiveness of the marine equipment industry, which accounts for approximately 55–65% of a vessel's prime cost, is a crucial element for strengthening the shipbuilding industry's competitiveness (Lee and Jang, 2018). The diffusion of smart factories through process improvements and cyber physical systems is one way to increase the competitiveness of the marine equipment industry (KOTRA, 2017).

With the global intensification of the fourth industrial revolution and the unforeseen COVID-19 pandemic, consumer behavior and lifestyles have changed. In response to these events, the adoption of new technologies that fuse ICT and related solutions, such as smart factories, has accelerated as firms strive to deliver products and services in more convenient and accessible formats. In response to this trend, a new stream of research on smart factories has been initiated in various countries, industries, and institutions. According to the German Research Centre for Artificial Intelligence, smart factories can be defined as production facilities that are operated intelligently through a close connection of the entire process based on smart IoT technology; factories that have intelligent production systems and integrate IT systems into traditional industries, such as the manufacturing industry for networked production. To assess the nature, challenges, and opportunities of smart factories, studies have emerged, including systematic literature reviews, to comprehend the factors that enable and constrain their development (e.g. Strozzi *et al.*, 2017; Osterrieder *et al.*, 2020; Forcina *et al.*, 2021). However, it has been found that studies on smart factories are mostly fragmented and narrow in their focus on peculiar technologies. Thus, scholars and practitioners are none the wiser when it comes to the conditions and antecedents of establishing smart factories within firms. In addition, studies exploring smart factories in marine equipment environments based on fuzzy-set Qualitative Comparative Analysis (fsQCA) are non-existent. Using this technique, this study expands the literature on the adoption of smart factories in the marine industry.

Specifically, this study addresses several gaps in the extant literature on smart factory adoption. Noting extant works on Industry 4.0 and smart factories, there seems to be a common view that our understanding of smart factories is still nascent and that the factors driving its adoption and implementation are largely unknown. Gobakhloo (2020:2385) stated that 'unfortunately, the current understanding of the mechanism through which manufacturers can ensure the successful implementation of these modern technologies in support of smart manufacturing is deeply limited.' Likewise, Thoben *et al.* (2017) highlighted the need for more research on Industry 4.0, as prior studies were neither comprehensive nor rigorous, while Oztemel and Gursev (2020) referred to the ambiguity surrounding the implementation of Industry 4.0.

Specifically, there appears to be a lack of understanding of the antecedents of smart factory implementation. Thus, Khin and Kee (2022) argued that the facilitators of Industry 4.0 have been under-researched. Osterrieder *et al.* (2020) noted the necessity for more research into the factors that influence the adoption of IoT applications in manufacturing noting the 'fragmented and spotty' literature on smart factory related research. Gillani *et al*. (2020) noted the limited understanding of the enablers of digital manufacturing and highlighted its complex nature. Hence, the present study presents fresh evidence to advance knowledge of the key factors shaping the implementation of smart factories (ISF hereafter).

Furthermore, considering the shortage of research exploring the antecedents of ISF, numerous scholars have solicited studies that exceed technology-related factors and have called for an examination of attributes such as institutional and human resource endowments affecting firms' adoption of smart technologies. Arcidiacono *et al*. (2022) argued that extant research on the antecedents of smart factory adoption has predominantly emphasized technological antecedents at the expense of managerial drivers. Strozzi *et al.* (2017) highlighted the need for more survey-based evidence to investigate the distinct roles of government support and firms' human resources in this process. Similarly, Giua *et al*. (2022) recognized the need to capture the impact of institutional factors on the implementation of smart technologies, as prior works disregarded this aspect. Gobakhloo (2020) summarized future studies to identify the organizational and environmental determinants of smart-factory implementation. Battistoni *et al*. (2023) stressed the need to examine both the human and managerial resources that may shape a firm's information processing capabilities. This is because, according to Fernando *et al*. (2022), in Industry 4.0, studies have mostly focused on technical and security factors. They drew attention to other determinants such as government policies and incentives. Hence, to address these voids, this study sheds light on the synergistic role of government support in concert with human resource factors (through managerial awareness and efficiency expectations) in predicting smart factory adoption.

Scholars have raised concerns about the robustness of methodologies employed in studies examining the adoption of smart technologies. In particular, there are appeals for the use of novel techniques to capture the complexity of smart technology adoption. This is based on the logic that this outcome is driven by combinations of factors as opposed to single influences. On this basis, Sony and Naik (2020) outlined the need for a greater understanding of critical success factors for Industry 4.0 adoption, and invited fresh evidence capturing interactions across such influences using quantitative evidence. Correspondingly, recent studies by Chatterjee *et al.* (2021) and Shen *et al.* (2021) explored combinations of environmental, technical, and organizational factors that are likely to increase the adoption of technology in manufacturing and production firms. Shang *et al*. (2021) acknowledged the limitations of techniques such as regression analysis in capturing interactions driving technology adoption and diffusion. Similarly, Giua *et al*. (2022) stressed the need to address the complexity of innovation adoption. Battistoni *et al*. (2023) suggested that the adoption of digital technologies emerges from a complex combination of paths. Therefore, using the novel fsQCA method, this study captures the complex interactions of ISF drivers to heed extant appeals on this matter. A complexity theory lens is espoused, arguing that firm behavior is shaped by a complex combination of interacting conditions. Kourouthanassis *et al*. (2016) noted that complexity theory addresses the limitations of existing approaches that merely capture single and isolated effects.

In summary, this study addresses existing voids and advances the literature by exploring the complex interactions underlying the implementation of smart factories [ISF] vis-à-vis government support, efficiency expectation, financial preparedness, and managerial awareness. Survey data from marine equipment manufacturers in South Korea were examined using a fuzzy-set Qualitative Comparative Analysis (fsQCA) developed by Ragin (2000). The fsQCA is a case-based analytical tool that can identify complex combinations of factors that lead to a given outcome (i.e., ISF). Accordingly, this study addresses two pressing research questions: (1) What environmental, technical, and organizational factors support the implementation of smart factories? (2) Are the factors influencing autonomous or heteronomous smart factory implementation?

The rest of the study is arranged as follows: Section 2 develops the conceptual framework through a literature review, while Section 3 describes the context of South Korea as the study's setting. Section 4 explains the method and instruments, and Sections 5 and 6 present the calibration, necessity, and sufficiency analyses, which are features of the fsQCA. Section 7 discusses the results. Finally, Section 8 concludes the study.

2. Conceptual Framework

2.1. Implementation of Smart Factories [ISF]

The implementation of IoT evokes the smartening of the manufacturing environment, and smart factories that are integrated with IT are a key feature of Industry 4.0, which focuses on creating smart products, procedures, and processes (Forschungsunion, 2013). In short, smart factories encompass key technologies, such as cyber-physical systems, IoT, big data, clouds, and AI.

The implementation of smart factories is fundamentally based on sociopsychological theories that address beliefs, attitudes, intentions of action, and practical behaviors regarding the acceptance of new information technology. Research on the causes of behavior in social psychology has expanded and begun to be applied to the technology acceptance process. To illustrate the process of embracing new information technologies and systems, theories such as the theory of planned behavior [TPB] (Ajzen, 1985, 1991), the technology acceptance model [TAM] (Davis, 1986, 1989; Davis *et al.*., 1989), unified theory of acceptance and use of technology [UTAUT] (Venkatesh *et al.*., 2003), diffusion of innovation [DOI] (Rogers, 1995), and technology organization and environmental framework [TOE] (Tornatzky and Fleischer, 1990; Oliveira and Martins, 2011) have previously been appropriated. Scholars have espoused these perspectives in a wide range of fields such as education, fashion, transportation, and e-commerce at the individual and corporate levels (Strozzi *et al.*, 2017; Cyr *et al.*, 2006; Tzou *et al.*, 2009; Wang *et al.*, 2020; Samar *et al.*, 2017; Rahman *et al.*, 2017; Min *et al.*, 2019).

The TAM, introduced by Davis (1986) and predicated on the Theory of Reasoned Action (Fishbein and Ajzen, 1975) was a specific attempt to describe the mechanisms of users' adoption of new technologies or systems. Subsequently, Davis *et al.* (1989) suggested a revised TAM to explore the stimuli motivating computer usage including two main factors of perceived Usefulness (PU) and perceived ease of use (PEU). PU is defined as the subjective likelihood that the use of a certain system will improve a user's actions, whereas PEU refers to the degree to which the potential user expects the target system to be effortless (Davis, 1989). This model has been extensively examined by various social groups to explain the introduction of various IT interfaces and products, and its explanatory power has been verified. Despite this volume of research, insights into the implementation and acceptance of smart factories based on existing validated models are underreported. Based on this premise, this study conceptualizes the adoption factors for the implementation of smart factories, which are a step away from existing automated production systems.

2.2. The Determinants of ISF

Factors enabling the implementation and acceptance of smart factories are at the centre of the ongoing paradigm shift in the marine equipment manufacturing industry. The selection of the main factors considered in this study was based on key technology acceptance theories, such as TAM (Davis, 1989) and TPB (Ajzen, 1991), a review of previous literature on firms' technology acceptance, and the characteristics of the marine equipment industry. Here, 'efficiency expectation' was selected to reflect TAM's perceived usefulness and TPB's attitudes while 'financial preparedness' was chosen to illustrate TPB's perceived behavioral control. Additionally, given the South Korean government's involvement in the marine equipment industry, 'government support' was also included. Lastly, in view of the large support in the empirical literature for the crucial role of 'top management support' when it comes to technology adoption, the latter was also incorporated. To confirm the relevance of these factors, pre-survey interviews were conducted with six marine equipment industry participants. Based on this process, it was confirmed that all factors are essential for understanding smart factory considerations in the marine equipment industry. These factors are successively appraised.

Government Support (GS)

Governments and the IT industry have championed smart factories. Government support is necessary for the successful implementation of smart factories, which are at the core of the manufacturing system in the Fourth Industrial Revolution. Strozzi *et al.* (2017) stated that research on governments and funding institutions regarding smart factories could confirm these entities as either enablers or obstacles to their diffusion. Nonetheless, they emphasized the need for further research in this area. Although studies assessing the role of government support in the implementation of smart factories are scarce (e.g., Won and Park, 2020), prior studies predicting product innovation have identified a significant causal relationship between government support, firms' sales growth, and market share (e.g., Merrifield, 1987; Doutriaux, 1991; Wang *et al*., 2021; Hu *et al*., 2021). Furthermore, these studies highlighted the need for strong government support and policies to achieve sustainability in the implementation of Industry 4.0 (e.g., Luthra *et al*., 2020; Majumdar *et al*., 2021; Verma *et al*., 2022).

Moreover, Choi and Choi (2017), Gil (2019), Ju and Lee (2019), and Stentoft *et al.* (2021) determined that government support positively influenced the implementation and acceptance of smart factories. In their empirical analysis, Choi and Choi (2017) hypothesized that government support positively affects the establishment of smart factories. Their results showed that after organizational participation, this factor predicted the establishment of smart factories. Furthermore, they stated that the formulation of policies to accommodate company size and peculiarities in the manufacturing environment is important when accessing government support. Choi and Choi (2017) also proposed the early introduction of a domestic standard certification model that can objectively diagnose and evaluate firms' level of manufacturing smartification.

In another study, Gil (2019) stated that government support is an important factor when SMEs naturally focus on return-on-investment reviews of smart factory investment opportunities.

Government support reduces the payback period, thereby positively influencing acceptance intention. Therefore, continuous government support is needed along with external specialist support, such as consultants, to increase SME's understanding of smart factories and establish a long-term roadmap to ensure timely investment and appropriate development of technology. Ju and Lee (2019) confirmed, based on prior studies, that government policy support provides substantial value to SMEs. They hypothesized that a company's willingness to access government support schemes positively influences the establishment of smart factories. Their ensuing analysis showed that government financial and system technology support measures empowered metal-processing SMEs facing the pressure of new equipment investment. They also proposed promoting an understanding of smart factories and providing financial and technological government support for future projects.

Entrepreneurial Spirit of Top Management (ESM)

The term 'entrepreneur' has become commonly used for financially successful individuals who have commercialized new technologies. Moreover, entrepreneurs who pioneer disruptive innovations that bring about new processes and products are called innovators (or creative destructors), and their nature is called the entrepreneurial spirit (Schumpeter, 1934). The spirit of entrepreneurship has changed from a start-up environment to an innovation in the organizational setting. Baron and Shane (2007) regarded the entrepreneurial spirit as a firm's exploration and implementation of something tangible or intangible to create value. Gartner and Baker (2010) viewed the entrepreneurial spirit as the process by which individuals pursue opportunities and improve corporate value through continuous innovation (Czop and Leszczynska, 2011). The OECD has developed the Global Entrepreneurship Index (GEI) to depict the entrepreneurial spirit of each country through attitudes, abilities, and aspirations. Based on the GEI's assessment, countries can seize business opportunities amid uncertainties and risks that otherwise hinder entrepreneurship. They can also create environments with thriving and enabling ecosystems. Accordingly, prior studies on entrepreneurial spirit have mostly examined the extent to which the degree of entrepreneurial spirit contributes to economic development (e.g. Caree *et al.*, 2007; Kelley *et al.*, 2011), while others have assessed its components of entrepreneurial spirit (e.g. Covin and Slevin, 1991, Hitt *et al.*, 2001).

Gil (2019) reasoned that the top management's entrepreneurial spirit was the main factor in smart factory acceptance; however, their results did not support this thesis. However, Choi and Choi (2017) found that top management had a positive influence on the establishment of smart factories, while Ju and Lee (2019) concluded that top management and members of the organization's willingness to participate had a positive influence on smart factory establishment. Choi and Choi (2017) stated that the resolution of top management is a crucial factor in the pursuit of company innovation and is especially important for SMEs. Their empirical analysis confirmed that this positively influences the establishment of smart factories. They further suggested that it is important for top management to share an understanding of and promotional strategies for smart factories with organizational members.

Furthermore, Ju and Lee (2019) combined top management, organizational members, and corporate willingness to participate in variables to predict the establishment of smart factories. Their analysis proved that corporate willingness to participate positively influenced outcomes. However, top management also has a high correlation with the establishment of a smart factory. Finally, although Gil (2019) initially thought that the entrepreneurial spirit might be a key factor in the adoption of smart factories; however, as this quality is a prerequisite for innovation and risk-taking in top management, they rejected this hypothesis in their empirical analysis.

Efficiency Expectation (EE)

Schmidt *et al.* (2015), Müller *et al.* (2018), Gil (2019), and Ju and Lee (2019) agree that expectations for improved production efficiency have a positive effect on smart factory implementation and acceptance. This is because smart factories improve product management and operational efficiency by upgrading existing systems, rather than installing new production lines. Thus, it must be viewed as a long-term investment, where the results are cumulative rather than immediate. As customer demands are considered in the production planning and product order stages, real-time changes can be made during manufacturing to reflect changes in customer preferences and enhance collaboration with manufacturers and distributors. Furthermore, remote production is made possible by utilizing real-time monitoring of facilities as well as remote control of equipment and production facilities.

Gil (2019) described expectations of improved production as a relative technological advantage; awareness of this is a factor in determining the adoption and acceptance of new technology offerings. Such relative advantages and additional value are determining factors in the implementation of smart factories. According to Schmidt *et al.* (2015), these relative advantages include factors such as production time improvements and mass customization.

Ju and Lee (2019) found that the establishment of a smart factory had a positive influence on corporate competitiveness, as measured in terms of an increase in sales, quality improvement, production time reduction, and an increase in customer demand. Other areas that may be augmented include a decrease in defective products and production costs. Likewise, Müller *et al.* (2018) hypothesized that strategy, operations, environment, and people are factors that promote the implementation of industry 4.0. Operational factors were explained through productivity improvements (such as efficiency improvements, cost reductions, quality improvements, and production time reductions). Their analysis showed that operations had a significant influence on the implementation of Industry 4.0.

Kim *et al.* (2019) employed an analytic hierarchy process [AHP] technique to study the factors that influence the implementation of smart factories in Korean SMEs, including broad categories of productivity improvement, image enhancement, marketing improvement, and cost reduction. Their findings indicated that image enhancement was the most important factor, whereas productivity improvement, which consisted of decreasing the percentage of defective products, increasing production output, and maintaining adequate inventory, was the least important.

Financial Preparedness (FP)

Financial preparedness is essential for sustaining a company's operations, and is one of the most important factors in ensuring long-term viability. This ensures the availability of funds for investment in innovative technologies and equipment upgrades (Iacovou *et al.*, 1995). Gil (2019), Ju and Lee (2019), and Hamada (2019) showed a positive relationship between financial preparedness and intention to implement or accept smart factories. Furthermore, Gil (2019) showed that financial preparedness has the largest standardized coefficient among the variables related to this outcome. Therefore, despite the potential return on investment, it is necessary to consider the depth of a firm's financial resources.

Ju and Lee (2019) regarded financial preparedness as essential for developing manufacturing capabilities. Their study showed that manufacturing capability has the greatest impact on smart factory implementation and firm size. In other words, manufacturing capability derived from financial soundness is enhanced as the size of the company increases, which has a positive influence on smart factory establishment. Hamada (2019) regarded sufficient financial resources as factors for investment in Industry 4.0 and correlated this with the company's revenue and operational stability. Their results showed that operational stability had a significant impact on the adoption of Industry 4.0. Even when a company's revenue is low, its stable operations would have a positive influence on exploring solutions to Industry 4.0.

2.3. The Determinants of ISF: A Configuration Approach with a Complexity Lens

From the preceding review, it appears that prior studies have overlooked the complex nature of the ISF. In fact, new evidence on firms' adoption of technology seems to suggest that this behavior is more nuanced than previously reported in the extant literature. It is also conceivable that a firm's adoption of technology is predicted by a complex interaction of factors rather than isolated drivers. Pappas *et al.* (2021) demonstrated that the willingness of Greek accommodation firms to adopt IoT innovations depends on the interplay of benefits, risks, and barriers. In Italy, Roffia and Mola (2022) reported that SMEs' implementation of ERP systems is determined by a combination of factors such as digital skills, the ability to manage ERP risks, and the strategic importance of ICT in the firm. In a study on IoT platforms, Abbate *et al.* (2019) concluded that SMEs' adoption of such platforms is shaped by a combination of key activities, resources, and partners.

In this regard, evidence exists from Chinese firms. For instance, Zhang *et al.* (2021) concluded that the adoption of cloud computing is predicted by a combined set of factors including government support, provider capability, relative advantage, and IT competence. Shen *et al.* (2021) found that consumer goods upgrading in Shanghai is driven by three combinations of technology, organization, and environmental factors: (1) human environment, (2) internal factor aggregation, and (3) technology–environment paths. Investigating big data, Sun *et al.* (2020) concluded that a combination of factors, including relative advantage and technology competence, affect Chinese firms' use of complex datasets. Finally, Xia *et al.* (2022) showed that Chinese firms' resilience in the digital era is driven by the constellations of entrepreneurial orientation, digital business capability, and digital business model innovation.

Therefore, consistent with prior evidence and inspired by findings in the Asian context, we anticipate that for South Korean firms, ISF is driven by a combination of government support, the entrepreneurial spirit of top management, efficiency expectancy, and financial preparedness. This view is underpinned by the complexity theory, which outlines the premise that the sought outcome is predicted by alternative combinations of factors. It also argues that, for an outcome to occur, the presence and absence of causal conditions depend on their combination with one another (Fiss 2011; Woodside 2013; Kourouthanassis *et al.*, 2016). Relationships among variables are complex and interdependent, which is often disregarded by variance-based approaches (Woodside, 2017). In contrast, the complexity view recognizes such complex interactions, along with the likelihood that different sets of interactions could lead to the same behavior, as per the so-called equifinality phenomenon. In the context of information system adoption, complexity theory has been used to argue that user adoption is explained by multiple configurations of factors, with some being sufficient when captured in combination and others being necessary but not sufficient for adoption to occur (Pappas and Woodside, 2021). Therefore, we contend that technology acceptance factors should be examined using a complexity lens. In addition, the adoption of a smart factory is governed by complex links among government support, the entrepreneurial spirit of top management, efficiency expectancy, and financial preparedness. This implies that factors such as government support may not have the same effect on the adoption of smart factories when combined with low efficiency expectations. Accordingly, we suggest the following proposition: *'The combined influence of government support, entrepreneurial spirit of top management, efficiency expectancy and financial preparedness is more likely to enhance ISF in comparison to isolated influences.'*

The research model is illustrated in Figure 1.

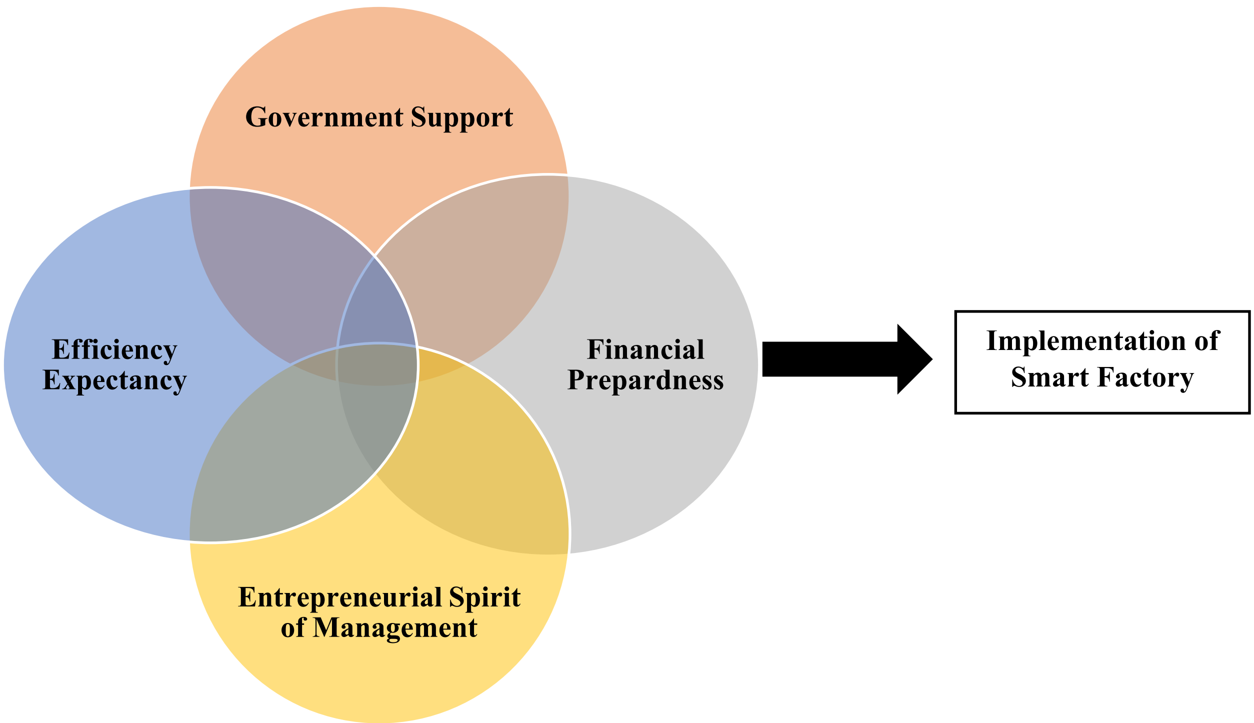

Fig. 1. Research Model

3. The South Korean Context

Economically, South Korea is the world's twelfth largest economy, with a GDP of $1.8 trillion (The World Bank Group, 2022a) and a population of 51.7 million (The World Bank, 2022b). It is deemed to be an industrialized and high-income country, thus qualifying as a member of the Organisation of Economic Cooperation and Development [OECD] (Lee and Cho, 2022). As a country, South Korea has experienced one of the largest economic transformations in the last 60 years owing, in part, to the diversification of its economy into diverse manufacturing industries including cars, electronics, steel, semiconductors, and shipbuilding (Santander, 2022). Known brands such as Hyundai Motors, Kia Motors, LG Electronics, and Samsung have accorded South Korea a positive global image in terms of its manufacturing prowess (Tsai *et al.*, 2021). Not surprisingly, manufacturing output of $456.60 billion accounted for 25% of the country's GDP in 2021, a noticeable increase of 12.4% from 2020 (The World Bank, 2022c). Comparatively, the impact of the COVID-19 pandemic on the South Korean economy was minimal owing to strict testing and isolation measures (Austermann *et al.*, 2020). Nevertheless, the government embarked on an expansionary fiscal spending program to stimulate the development of new industries and harness the potency of data, networks, and AI (Santander, 2022). Thus, the South Korean government actively promotes the digital transformation that manifests in smart factory operations. Despite significant trends impacting the marine equipment sector, such as the COVID-19 pandemic and the new International Maritime Organization [IMO] regulations, there remains a dearth of research in this industry, as highlighted by a recent OECD (2023) study. To address this shortcoming, this study offers evidence with theoretical implications from a leading player in marine equipment space. South Korea's unique manufacturing profile and its economic and fiscal undercurrents make it an ideal setting for investigating the drivers of ISF.

4. Method

This study investigates how government support, managerial awareness, financial preparedness, and efficiency expectations mutually impact the implementation of smart factories in South Korea's marine equipment industry. The marine equipment industry produces all the machinery and materials used in the construction and repair of ships, and "*this industry includes the design and manufacture of equipment that are supplied and necessary in ships, such as power and propulsion equipment, auxiliary machinery, navigation and communications equipment, mooring and unloading equipment, and residential and safety* *equipment* (KOTRA, 2020, p.1). The demand for eco-friendly ships is expected to increase owing to new regulations enacted by the IMO under the auspices of the United Nations. Because the Korean marine equipment industry is of strategic importance to the national economy, national and local governments are actively supporting the introduction of smart factories.

Using non-probability convenience sampling, a survey was distributed to managers working in the marine equipment industry, from employees to executives and CEOs, whose firms are listed in the Korea Marine Equipment Association (KOMEA). An initial participation request was circulated via email. A web-based survey was distributed to avoid omissions and duplicate responses. A total of 180 valid responses were collected and returned via email. The measures used are presented in the Appendix along with their sources. All items were assessed on a 5-point Likert scale.

The participants' profiles are listed in Table 1. Most managers were male (89.4%), mostly in their 40s (42.2%) and 30s (28.3%). Most (50.5%) also had between 5 and 14 years of work experience in positions, including deputy manager, deputy department head, head of department, and section chief. They worked in companies that mostly employed fewer than 50 people (57.2%) and had smart factory implementation activities ranging from 'not yet applied' to 'advanced.'

Table 1. Participants' Profile

Category		**Frequency (Number)**	**Percent (%)**
Gender	Male	161	89.4
	Female	19	10.6
Age	20s	7	3.9

	30s	51	28.3
	40s	76	42.2
	50s	33	18.3
	Over 60s	13	7.2
Work Experience	Below 5 years	39	21.7
	5 – 9 years	42	23.3
	10 – 14 years	49	27.2
	15 – 19 years	16	8.9
	Over 20 years	34	18.9
Position	Deputy manager	36	20
	Deputy Department Head	30	16.7
	Head of Department	29	16.1
	Section Chief	62	34.4
	Others	23	12.8
Department	Production	11	6.1
	Planning	8	4.4
	Procurement	9	5.0
	Management	47	26.1
	Marketing	81	45.0
	Others	24	13.3
Revenue [in KRW]	Below 10B	87	48.3
	10B – 30B	44	24.4
	30.1B – 50B	10	5.6
	50.1B – 100B	14	7.8
	100.1B – 300B	16	8.9
	300.1B – 500B	6	3.3
	500.1B – 1T	3	1.7
	Over 1T	0	0
Number of employees	Below 50	103	57.2
	50 – 100	33	18.3
	101 – 500	35	19.4
	501 – 1000	5	2.8
	1001 – 3000	3	1.7
	Over 3000	1	0.6
Smart factory implementation stage	Not yet applied	91	50.6
	Basic	57	31.7
	Intermediate 1	29	16.1
	Intermediate 2	2	1.1
	Advanced	1	0.6

5. Constructs' Reliability and Validity

Prior to conducting the fsQCA, the reliability and validity of the constructs were assessed. In this study, a structural equation modelling protocol was applied using WarpPLS version 8.0 (Kock, 2022). Reliability was tested through the Composite Reliability (CR) and Cronbach's

Alpha (α), whereas validity was examined through the Average Variance Extracted (AVE) and factor loadings of the convergent validity, and the square roots of AVEs for the discriminant validity. Collinearity was assessed using the variance inflation factor (VIF) (Hair *et al.*, 2016). Table 2 depicts the results of the measurement model, indicating satisfactory scores in terms of reliability (CR and α values below the 0.7 threshold), convergent validity (AVE scores above 0.5 cut-off and all loadings above 0.6 as shown in Appendix) and collinearity (VIF levels below or equal to 5). Discriminant validity is also confirmed, given that the AVE square roots are greater than the diagonal (Hair *et al.*, 2011). These scores suggest a good measurement quality.

Table 2. CR, α, AVE and VIF

Factor / Variable	Financial Preparedness	Government Support	Entrepreneurial Spirit of Management	Efficiency Expectation	ISF
CR	0.91	0.91	0.94	0.93	0.96
α	0.88	0.87	0.92	0.91	0.95
AVE	0.69	0.67	0.78	0.75	0.85
VIF	3.12	2.81	2.34	2.15	5.11

6. fsQCA Analysis

The fsQCA is based on a Boolean algebra system that captures a set of conditions, often in the form of combination(s) that lead to a given outcome (Fiss *et al.*, 2013; Ordanini *et al.*, 2014). This technique includes contrarian cases that deviate from the general trend of the data (Woodside, 2014), thus minimizing the issues of unobserved heterogeneity (Schneider and Wagemann, 2010). Furthermore, the fsQCA was developed by Ragin (2000), and software version 3.0, (Ragin and Davey, 2016) was used in this study.

The technology adoption literature mostly adopts the key success factor [KSFs] approach to predict the factors leading to technology acceptance. Typically, using traditional regression-based techniques, such as multiple regressions and structural equation modelling, the KSFs approach captures the isolated effects of various antecedents. Instead, fsQCA can be described as the key success paths [KSPs] approach wherein several paths composed of combined effects lead to technology adoption (Cheng *et al*., 2013). In short, fsQCA offers comprehensive insights by uncovering (1) multiple solutions that can successfully lead to the same outcome (equifinality) and (2) complex causality issues by capturing latent interactions across a set of antecedents (Schlittgen *et al*., 2016; Wong *et al*., 2018). In terms of philosophy, unlike conventional regression-based techniques, which are typically based on a deductive reasoning, fsQCA espouses an abductive approach which aims to provide an 'inference to the best explanation based on the available evidence' (Thomas *et al*., 2014: 12). The fsQCA advances ontological realism, where causal inference is generated from empirical findings (consistent set relationships) by considering the knowledge of cases and the context to provide plausible explanations (Rutten, 2021). This approach does not minimize the utility of other statistical techniques. Rather, it offers a complementary procedure for understanding antecedents and outcomes.

6.1. Calibration

This is the first step in the fsQCA analysis. The Likert scale values were transformed into fuzzy scores. This was done by identifying three qualitative thresholds representing the fuzzy set scores and their corresponding values in the data (Ragin, 2009). The three thresholds are (1) full membership, (0.5) crossover point, and (0) full non-membership (Ragin, 2009). The three corresponding thresholds were identified based on the 95th, 50th, and 5th percentiles. However, Greckhamer *et al.* (2018:489) argued that "sample-based calibration should be avoided whenever possible." In the case of the Likert scales, the thresholds can be 4 [agree], 3 [neutral], and 2 [disagree] (Pappas and Woodside, 2021) or 5 [strongly agree], 3 [neutral], and 1 [strongly disagree] (Laouiti *et al.*, 2022). In this study, the latter threshold precedent was selected to represent non-membership, the crossover point, and full membership.

6.2. Necessity Analysis

This step follows the calibration process. The conditions (or variables) deemed necessary for ISF were identified. A necessary condition means that its presence is required, but may not be sufficient for the outcome to occur (Kent, 2015). Necessity is confirmed when a condition exhibits a consistency score of at least 0.9 (Legewie, 2013). Consistency reflects the degree to which cases in the sample that share a condition or configuration agree to display the desired outcome (Ragin, 2008). Table 3 shows that Government Support, Entrepreneurial Spirit of Management, and Efficiency Expectation are deemed necessary for ISF to occur, although ESM and EE have the highest scores. This needs to be confirmed through a sufficiency analysis.

Table 3. Necessity Analysis

	Consistency	**Coverage**
Financial Preparedness	0.85	0.87
~ **Financial Preparedness**	0.56	0.55
Government Support	0.92	0.81
~ **Government Support**	0.49	0.57
Entrepreneurial Spirit of Management	0.97	0.72
~ **Entrepreneurial Spirit of Management**	0.37	0.57
Efficiency Expectation	0.97	0.71
~ **Efficiency Expectation**	0.41	0.66

6.3. Sufficiency Analysis

Once the necessary conditions were determined, a sufficiency analysis was conducted. In this step, the combinations (if any) leading to ISF were identified. This was accomplished by generating truth tables containing logically possible combinations of conditions (Ragin *et al.,* 2008a). To identify the relevant configuration for the sought outcome, thresholds for the minimum number of cases associated with those combinations [known as the frequency threshold] and the appropriate consistency score [known as the consistency cut-off] were set (Woodside and Zhang, 2012). In this study, the former was set to four cases, in line with Ragin's (2008) suggestion to use higher thresholds than one case for larger samples. For the latter, a cutoff value of at least 0.80 was used. According to Ragin (2008), the consistency score for the combination should be at least 0.75 for the combination to be consistent.

Typically, fsQCA provides three types of solutions: parsimonious, complex, and intermediate. However, Kent (2015) recommended interpreting an intermediate solution as the midpoint between parsimonious and complex solutions. The results are summarized in Table 4. For clarity, a simple representation of the black and white circles is used. Black and white circles indicate the presence and absence of causal conditions, respectively. Blank cells illustrate the cases in which the presence or absence of such conditions did not affect the outcome.

Table 4. Sufficiency Analysis
Model: ISF = f(FP, GS, ESM, EE)
Algorithm: Quine-McCluskey

Solutions	ESM	EE	GS	FP	Raw Coverage	Unique Coverage	Consistency
1	●	●		⬤	0.83	0.03	0.91
2	●	●	⬤		0.89	0.08	0.87
Solution coverage					0.92		
Solution consistency					0.86		

Frequency Cutoff: 4, Consistency Cutoff: 0.83

As shown in Table 4, each combination is accompanied by scores for consistency and coverage. Similar to the significant value in multivariate techniques, consistency reflects "*the degree to which the cases sharing a given combination of conditions . . . agree in displaying the outcome in question.*" Coverage reflects "*the degree to which a cause or causal combination 'accounts for' instances of an outcome*" (Ragin, 2008:44), and indicates the empirical importance of sufficient configurations (Ordanini *et al.*, 2014). Coverage can be raw or unique. Raw coverage can overlap with other combinations, whereas unique coverage is exclusive to certain combinations (Beynon *et al.*, 2016). The overall solution coverage is also presented to indicate the extent to which the outcomes can be determined by a set of configurations [akin to the R-square value in multivariate methods] (Woodside, 2014). In addition, core and complementary (peripheral) conditions were identified. Core conditions exhibit a strong causal association with outcomes, while peripheral elements exhibit a weaker association (Fiss, 2011). Core conditions are highlighted in bold.

As shown in Table 4, two configurations associated with high ISF emerged. Both involve high levels of ESM and EE (confirming their necessity), with the first combination adding FP as the third condition, and the second configuration involving GS instead. Here, the GS and FP are the core conditions. Hence, it seems that while the ESM and EE pair is required for ISF, it is not sufficient and requires either GS or FP, suggesting that these two aspects [GS and FP] can substitute for each other. From the raw coverage scores, the two combinations bear relatively similar empirical relevance, although the second configuration exhibits slightly higher relevance. The overall solution coverage was 0.92, reflecting the proportion of the ISF covered by the two solutions.

6.4. Negation Analysis

The fsQCA is an asymmetric analysis and therefore allows researchers to identify the conditions yielding the absence of the outcome in question, that is, the ISF (Kent, 2015; Woodside and Zhang, 2013). The principle of causal asymmetry assumes that the presence of an outcome can differ from the conditions that predict the absence of the same outcome (Pappas and Woodside, 2021). The negation analysis presented in Table 5 depicts the combinations that led to the absence of ISF. Accordingly, two possible combinations emerged. While the first involves low levels of ESM, FP, and GS, the second included high levels of both ESM and EE yet with a low level of GS. In other words, the presence of EE and ESM can be considered a double-edged sword. When combined with the absence of GS, this leads to a low ISF. Moreover, it appears that the absence of a GS is a core condition for a low ISF. The two solutions are relatively similar in terms of empirical relevance and have an overall coverage of 0.72.

Table 5. Negation Analysis

Model: ~ISF = f(FP, GS, ESM, EE)
Algorithm: Quine-McCluskey

Solutions	**ESM**	**EE**	**GS**	**FP**	**Raw Coverage**	**Unique Coverage**	**Consistency**
1	○		◯	○	0.56	0.14	0.98
2	●	●	◯		0.58	0.15	0.90
Solution coverage					0.72		
Solution consistency					0.91		

Frequency Cutoff: 4, Consistency Cutoff: 0.90

In summary, the fsQCA demonstrated the complexity of the underlying interactions across the determinants of ISF. This outcome has been found to be predicted by the combinations of factors (or conditions) highlighted below:

1. The implementation of a smart factory is a complex equifinal behavior shaped by multiple combinations of conditions.
2. The entrepreneurial spirit of management and efficiency expectancy appear to be necessary (yet insufficient) conditions for ISF to occur.
3. Government support and financial preparedness are core conditions that are yet to be substituted. ISF is likely to be high when one of these is combined with the entrepreneurial spirit of management and efficiency expectancy.

4. If high levels of entrepreneurial spirit of management and efficiency expectancy are combined with the absence of government support, a reverse effect will occur; that is, the absence of ISF will be more likely to occur.
5. The absence of government support is a core condition for the absence of ISF.

7. Discussion and Theoretical Implications

Using a novel configuration approach, this study uncovered the complex combinations of government support, entrepreneurial spirit of top management, efficiency expectations, and financial preparedness driving the implementation of smart factories in South Korea. This confirms the assumption that a firm's adoption of smart factories is a complex equifinal behavior shaped by multiple combinations of conditions. This has important implications for the future applications of theoretical frameworks in technology adoption. The current findings suggest that these models should move away from a linear and net effect approach towards a more complex lens capturing synergies across technology adoption drivers and discerning the equifinal combinations of factors.

Specifically, the findings reveal two key paths that are likely to lead to high adoption of smart factories, along with two additional solutions that are likely to cause low adoption. Such findings advance the extant Industry 4.0 literature by addressing (1) the shortage of studies on the adoption of smart factories highlighted by Osterrieder *et al.* (2020), Thoben *et al.* (2017), Sony and Naik (2020) and Oztemel and Gursev (2020), (2) the non-existent corpus on the synergistic role of government support and human resource factors outlined by Strozzi *et al.* (2017), and (3) the need for more holistic insights on the complexities underlying smart factor adoption in response to Sony and Naik (2020), Chatterjee *et al.* (2021) and Shen *et al.*'s (2021) contention. These findings echo recent evidence suggesting that firms' technology adoption behavior is a complex attribute triggered by the combined influence of various factors (Pappas *et al.* 2021; Roffia and Mola, 2022; Abbate *et al.* 2019), along with evidence from Asia (Zhang *et al.*, 2021; Shen *et al.*, 2021; Sun *et al.*, 2020; Xia *et al.*, 2022).

Among the generated combinations, several key patterns require further investigation. First, for high adoption, the presence of top management's entrepreneurial spirit and efficiency expectations are necessary conditions, although these are not sufficient by themselves because other factors are also needed. The importance of these two conditions reflects prior studies, such as Khin and Kee (2022), Gil (2019), Schmidt *et al*. (2015), Ju and Lee (2019), and Müller *et al*. (2018). These studies suggested that expectations of improved production (equivalent to efficiency expectations) and expected benefits are key to driving smart-factory implementation and acceptance. Similarly, several previous studies have confirmed the importance of top management leadership and appetite for innovation as determinants of smart factory adoption (Choi and Choi, 2017; Ju and Lee, 2019). However, the findings also revealed that these two factors are not sufficient and must be accompanied by either government support or financial preparedness to effectively drive high ISF. In this regard, aspects such as government support and financial resources are deemed core factors that provide firms with the capability to implement smart factories and Industry 4.0 (Gil, 2019; Ju and Lee, 2019; Hamada, 2019). Similarly, the findings echo Choi and Choi (2017), Ju and Lee (2019), and Stentoft *et al.* (2021) who concluded that government support positively influences the implementation and acceptance of smart factories. However, it has also been shown that financial preparedness and government support can be substitutable, as, in addition to management's entrepreneurial spirit and efficiency expectations, firms need either government support or financial preparedness to adopt a smart factory. Thus, it is argued that firms with financial preparedness may not need external intervention, whereas firms in need of financial support rely on government intervention to realize ISF. By contrast, when financial preparedness is present, firms may not need government intervention. This is somewhat commensurate with the qualitative evidence offered by Khin and Kee (2022), suggesting that when firms exhibit strong financial capabilities, they do not need government intervention to adopt Industry 4.0.

Notwithstanding these telling predictions, our findings seem to indicate that when the absence of government support coincides with a high entrepreneurial spirit among managers and high efficiency expectations, low adoption is likely to occur. This outcome is intriguing and may suggest that when firms are committed to Industry 4.0 but lack support, a reverse effect could occur because efforts to initiate technology may lead to frustration and a longer return on investment. This discourages firms from implementing it. In this regard, Gil (2019) explained that, particularly for smaller firms, return on investment is an important consideration when venturing into technology adoption and that government support is a way to accelerate this process. Therefore, while financial preparedness and government support may be substitutable, one may conclude that government support is particularly important, and its absence may be detrimental to Industry 4.0. Majumdar *et al*. (2021) opined that Industry 4.0 is a policy-driven framework in which government support is crucial. Moreover, Luthra *et al*. (2020) and Verma *et al*. (2022) argued that strong government intervention and policies are key to the sustainable implementation of Industry 4.0.

8. Practical Implications

Caution should be exercised when making generalizations from a country-specific analysis as distinct market, environmental, and cultural idiosyncrasies may influence observed outcomes. However, the marine equipment industry, such as the shipbuilding sector, interacts with suppliers and competitors in global networked operations. Therefore, the conclusions drawn here could suffice in neighboring countries, such as China and Japan, where there is also a high adoption of smart factories. Moreover, the inherent quantitative design offers a greater likelihood of generalizable findings. However, limitations in external validity may impair the generalizability of this study. To tackle this, the research model and measures should be replicated in neighboring countries where there is a growing adoption of smart factories to minimize the possibility of survey errors. Comparing future findings with those of this study will advance the literature.

In short, the findings show that the adoption of a smart factory is a complex behavior, underlined by the presence of several factors and equifinal paths. Therefore, policymakers should adopt a comprehensive approach to address these issues, as well as a tailored approach depending on the firm's financial capability. To foster the adoption of smart factories, policymakers may organize awareness campaigns on the benefits of smart factories, given that the expected benefits are an important factor. Similarly, ISF consultants can be trained and assigned to firms to help managers develop an entrepreneurial spirit to yield the expected benefits. However, these two aspects are inadequate. Policymakers should also aim to identify firms that are not financially capable so that they can be provided with funding and other types of support to implement smart factories. Our findings reveal that financially prepared firms may not need such an intervention; instead, they will only require awareness campaigns and ISF consultants to boost their entrepreneurial spirit and expected benefits.

As mentioned earlier, enhancing the competitiveness of marine equipment companies is essential for improving the overall competitiveness of the shipbuilding industry. Considering the global manufacturing paradigm shift, the introduction of smart factories into the marine equipment industry is likely to continue. However, marine equipment companies face an increased financial burden owing to the difficult environmental conditions arising from global headwinds, including COVID-19. In addition, Asian marine equipment companies are mainly small and medium-sized enterprises, making operations more challenging.

Therefore, the results of this study are valuable for tailoring firms' ISF drivers to the characteristics of available government support, financial power, entrepreneurship, and efficiency expectations. Furthermore, it provides valuable insights for the Korean government and other neighboring governments that need to support this innovation, by creating a smart marine equipment manufacturing platform, and supporting this change strategically in the long run. It is expected that it will be possible to promote and induce each firm's participation through continuous consulting and training programs tailored to each firm. Ultimately, it is anticipated that this study will inform the development of a cooperative ecosystem in which the government, academia, and private firms can create synergies for smart factory implementation in the marine equipment sector.

9. Limitations and Future Studies

Despite the substantial contributions of this study, it has a few limitations. First, the study captures four key conditions likely to trigger smart factory adoption. However, this does not exclude additional factors that could be important in this process, such as resources, skills and support, human resources, knowledge, technical factors, training (Khin and Kee, 2022), R&D, and management commitment (Majumdar *et al*., 2021). Future studies should consider these factors. Second, while we believe that the findings are applicable to South Korea and similar contexts, the sampling was based on a non-probability approach and was limited to 180 cases; hence, the findings should be generalized only with caution. Future studies should include larger sample sizes. Third, all references to causality in this study are based on theoretical assumptions. Owing to their cross-sectional nature, such causality claims should be made with caution. Despite their challenging nature, longitudinal studies should be conducted to confirm causality. Finally, it is important to develop new technologies and determine how to introduce and diffuse them. To address these issues, this study derives empirically significant results by adopting a configural approach related to the introduction of smart factories for digital transformation of the marine equipment industry. However, this can be regarded as a limitation of the present study. This limitation exists because to achieve innovation through digital transformation, where individuals and companies enjoy a win-win relationship, it is necessary to investigate practical obstacles, success factors, and best practices when promoting digital transformation. In addition, innovation through the introduction of new technologies requires process approaches that depend on the level of preparation and maturity of individual companies, bearing in mind that these innovations are not completed at once but in several iterations. Therefore, researchers should pay more attention to the day-to-day obstacles that employees and organizations face when implementing and diffusing smart factory solutions.

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Appendix: Items and Loadings

	Loading	Reference
Efficiency Expectation Factors		
It is known that implementing smart factory will enhance factory operation efficiency	(0.888)	Choi and Choi (2017), Ju and Lee (2019), Gil (2019), Lee (2008)
It is known that implementing smart factory will enhance product quality	(0.873)	
It is known that implementing smart factory will help decision making process	(0.844)	
Implementing smart factory will increase the revenue	(0.871)	
It is known that implementing smart factory will provide more opportunities for new business	(0.869)	
Financial Preparedness Factors		
Our company currently runs the business safely	(0.717)	Choi and Choi (2017), Ju and Lee (2019), Park (2019)
Our company has secured necessary financial support for smart factory implementation	(0.900)	
Our company established finance budget invest in smart factory implementation	(0.900)	
Our company is willing to transfer the other investment budget to smart factory implementation	(0.850)	
Our company is able to procure external budget if needed for smart factory implementation	(0.794)	
Government Support Factors		
Our company is aware of government's smart factory support scheme	(0.787)	Gil (2018), Ju and Lee (2019), Müller et al. (2018)
Government has various support scheme on smart factory implementation	(0.897)	
Government's smart factory support scheme is detailed and stable	(0.861)	
Government's smart factory support scheme is important to enhance our company's global competitiveness strategy	(0.761)	
Our company is willing to participate on government's smart factory implementation scheme	(0.790)	
Entrepreneurial Spirit of Top Management		
Our company's senior managers are strong-minded for innovation	(0.888)	Gil (2019), Hamada (2019), Ju and Lee (2019)
Our company's senior managers are highly acceptable to external ideas and innovations	(0.904)	
Our company's senior managers tolerate the issues arise from innovation process	(0.863)	
Our company's senior managers are highly interested in implementing/accepting smart factory	(0.892)	
Our company's senior managers are strong-minded in implementing/accepting smart factory	(0.868)	
Implementation of Smart Factory		
Our company is actively collecting smart factory implementation information	(0.927)	Gil (2019), Park (2019)
Our company is willing to implement smart factory	(0.908)	
Our company is planning to enhance the factory standard after smart factory implementation	(0.911)	

Our company is planning to establish investment budget on smart factory implementation	(0.957)	
Our company has recognised smart factory implementation as one of the important strategy	(0.932)	