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Sustainable Human–Machine Collaborations in Digital Transformation Technologies Adoption: A Comparative Case Study of Japan and Germany

Young Won Park [1,*] and Junjiro Shintaku [2]

1 Graduate School of Humanities and Social Sciences, Saitama University, 255 Shimo-Okubo, Sakura-ku, Saitama 3388570, Japan
2 Graduate School of Economics, The University of Tokyo, 3-34-3 Hongo, Bunkyo-ku, Tokyo 1130033, Japan
* Correspondence: ywparkjp@gmail.com; Tel.: +81-48-858-3337

Abstract: The Digital Transformation (DX) megatrend is fundamentally disrupting and changing the nature of work, business, and industry at a rapid pace. Although the notion of DX has garnered much research interest from practitioners, scholarship on this topic is somehow lagging behind, possibly because of the lack of theoretical frameworks on DX. Recently, most Japanese firms have begun to use diverse digital technologies to sustain their competitive advantages. However, the return of investment on digital technologies has not been as high as expected for some firms. Furthermore, as the visions of Industry 5.0 describe sustainable, resilient, and human-centered future factories that will require smart and resilient capabilities both from next-generation manufacturing systems and human operators, it is necessary to design resilient human–machine collaborations within factories. To this end, this paper presents a research model between DX technologies and scientific problem-solving in terms of deduction, induction, and abduction inference structures as an approach to resilient human–machine collaborations. The purpose of this research is to analyze the difference in the utilization pattern of the digital technology of American, German, and Japanese firms based on three types of decision-making methods. Next, we apply this framework in a comparative case study of two Japanese firms and one German firm, where we find that there is a difference in DX technologies utilization among the Japanese and German firms. We assert that the utilization of IoT technology in the United States and Germany is pursuing IoT with the aim of autonomous control, whereas Japanese firms prioritize robot–human collaboration. Finally, we discuss how our findings contribute to the burgeoning field of resilient human–machine collaborations by showing the distinct roles of deduction, induction, and abduction inference structures. Furthermore, our research contributes to international comparative studies to identify the difference in national IT utilization. Lessons and implications are discussed.

Keywords: sustainable human–machine collaboration; Digital Transformation (DX) technologies; case study; Japanese firms; German firm; international comparison

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1. Introduction

The Digital Transformation (DX) megatrend, which means using data and digital technologies to transform products, services, and business models based on the needs of customers and society as well as transforming operations themselves to establish a sustainable competitive advantage, is fundamentally disrupting and changing every industry, business, and jobs at a rapid pace. In Japan, as in other countries, the effects of DX have pervaded not only management but also all aspects of life. This is illustrated in the country's Society 5.0 initiative that was launched in 2016, with plans that far exceed Germany's Industry 4.0 (the fourth industrial revolution) vision. The continuing integration of DX technologies with business and organizational activities, processes, competencies, and models are embodied in a wide range of digital technologies such as big data and robots as well as the Internet of Things (IoT) and Wearables, Artificial Intelligence (AI) and Machine Learning (ML) [1,2]. Most Japanese firms also utilize diverse digital technologies to sustain their competitive advantages in the digital era.

However, very often, the firms do not see a significant return of investment on their investment in digital technologies. As discussed, DX is crucial in every industry. It is also important at all manufacturing sites. In particular, an appropriate promotion of digitalization in factories will also make it possible to improve work efficiency, streamline production lines, and reduce defective products and inventories [3]. Furthermore, DX facilitates the effective utilization of the earth's limited resources, contributing to reducing the environmental footprint. One study corroborates these concepts through case studies and suggests that promoting the digitalization of operations through IoT investments is essential to make production activities and supply chains sustainable in situations where human mobility is limited [3]. Furthermore, they posit the potential for IoT implementation and digitalization of operations to increase firms' resilience to various risks. This is a highly coveted capability, considering the increasing need to enhance the sustainability of production activities and supply chains [4].

However, if top managers implement and push for DX to operators, there might be resistance on the shop floor. CEOs might think this is simply resistance to change. But, if a good site of the factory that has accumulated its own capabilities based on the Toyota Production System (TPS) resists such a one-sided push, it cannot show its effectiveness. Furthermore, as the visions of Industry 5.0, which is the next version of Industry 4.0, describe sustainable, resilient, and human-centered future factories that will require smart and resilient capabilities both from next-generation manufacturing systems and human operators, it is necessary to design resilient human–machine collaborations within factories [5,6].

Thus, this paper presents a research model integrating DX technologies and scientific problem-solving in terms of deduction, induction, and abduction inference structures as an approach to resilient human–machine collaborations.

Meanwhile, the Japanese firms have achieved their current level of manufacturing excellence mostly by doing simple things (i.e., Kaizen) but doing them very well and slowly improving them over time [7–9]. As a result, they have accumulated tacit knowledge in the process of continually upgrading their manufacturing capabilities in factories from analog times. In recent years, they have invested in DX technologies to accelerate such problem-solving capabilities in their factories. In the environment of DX, the installation of a vast number of sensors in global mobile networks allows firms to collect relevant data in real time for value creation and productivity improvement. In addition, in a previous study, the research group argues that the utilization of DX technology varies across countries, industries, and companies [10]. The purpose of this research is to analyze the difference in the utilization pattern of the digital technology of American, German, and Japanese firms based on three types of decision-making methods. Thus, we hypothesize that there might be a difference between IoT use of Japanese and western firms.

Although the notion of DX has garnered much research interest from practitioners, academic achievements are somehow lagging behind, possibly because frameworks for DX are still nascent and evolving [11]. Specifically, much less work has been performed on sustainable human–machine collaborations. Though actor–network theory can help understand how a dynamic human–machine team works and how it evolves over time, currently, it has not been studied theoretically nor empirically [5]. Thus, in this article, we tried to address that gap by conducting exploratory research to suggest a scientific problem-solving model in terms of deduction, induction, and abduction inference structures as an approach to resilient human–machine collaborations and to show national differences in utilizing DX technologies. For this, we used exploratory case studies of two Japanese firms and a German firm.

2. Literature Review

2.1. Toyota Production System (TPS) and Sustainable Human–Machine Collaborations

Integrating the effort of diverse players across the engineering and supply chain is an important theme of value chain management (VCM) and supply chain management (SCM) [12–14]. Suppliers and customers work as partners for the common objective of enhancing competitiveness and profitability for the whole value and supply chain network [15]. Thus, value creation in engineering and the supply chain depends on effective information flows. Key success factors for a supply chain are effective management of strategic alliances through an inter-organizational information system that enables more accurate demand forecasting, inventory management, and other transactional activities and procurement processes [12–14,16–18].

Increasingly, a turbulent business environment requires firms to integrate their internal and external value/supply chain activities through strategic and operational information sharing. The construction of an appropriate IT system is indispensable in the design and implementation of corporate strategy [12–14].

In particular, the manufacturing industry is undergoing a transformation. It is no longer true that developing countries are the world's factories. Now the main roles are played by developed countries which possess skills in production technology and IT utilization, such as Japan, Europe, and the USA [19]. For example, in Germany, a manufacturing reform project conducted by industry, government, and academia started in 2011 with 'Industry 4.0' as a slogan [19–21]. They are making efforts to establish 'Smart Factories' that manage supply chains efficiently and autonomously by connecting data from within factories with enterprises.

However, the basis of Japanese integrated manufacturing is the collection of tacit knowledge in the field. Hence, translating the tacit into explicit and codified knowledge is one of the critical issues [10]. Skills and know-how that enable advanced matching from product development to product production have been accumulated in Japanese firms so far [9]. These skills and know-how have been passed on to junior staff from senior staff in the company through on-the-job training (OJT). During the high-growth period, it became established as a unique organizational skill transmission and organizational learning system in Japan. A representative Japanese integrated manufacturing concept is the Toyota Production System (TPS) [22–27] and lean manufacturing system or lean production system [7,8,15,28–36]. TPS is based on the philosophy of the complete elimination of all waste in pursuit of the most efficient methods [19,23,26,27]. TPS has evolved through many years of trial and error to improve efficiency based on the Just-in-Time (JIT) concept developed by Kiichiro Toyoda, the founder (and second president) of Toyota Motor Corporation. Waste can manifest as excess inventory, extraneous processing steps, and defective products, among other instances. All these 'waste' elements intertwine with each other to create more waste, eventually impacting the management of the corporation itself.

According to Toyota Motor Corporation, TPS is a way of making things that are sometimes referred to as a 'Lean Manufacturing System (or Lean Production System)' or a 'JIT system' and has come to be well known and studied worldwide [22–27]. According to the results of the international comparative analysis of the production system of automobile companies that a research group compared the original attitude of Japanese companies (typically TPS) with those of European and American companies, the characteristics of high-performance firms were identified and conceptualized as a 'Lean Production System' [18]. In the sluggishness of the American manufacturing industry in the 1980s, interest in the Monozukuri (Japanese manufacturing) of growing Japanese companies increased, and simultaneously studies on the 'Lean Production System' supporting its success shown in European and American firms increased [24,25,28]. Even within the automobile industry, there are differences in the complex system of products, and there is difficulty in correcting performance error data [24,25]. Womack et al. (1990) had a great influence on subsequent research and suggested the concept of a Lean Production System [28]. Notably, these works have demonstrated that differences in the management and strategy of development and production organizations contribute to differences in performance (even after controlling for the predictive power of country and culture).

This production control system in Toyota was established based on many years of continuous improvements, with the objective of making the vehicles ordered by customers in the quickest and most efficient way to deliver vehicles as swiftly as possible [23,27]. TPS was established based on two concepts: (i) 'Jidoka', which can be loosely translated as "automation with a human touch" and (ii) the 'JIT' concept, in which each process produces only what is needed for the next process in a continuous flow. Based on these foundational philosophies of Jidoka and JIT, TPS can efficiently and quickly produce vehicles of sound quality, one at a time, that fully satisfy customer requirements. TPS and its approach to cost reduction are the wellsprings of competitive strength and unique advantages for Toyota.

For Toyota, Jidoka means that a machine must stop safely whenever an abnormality occurs. Hence, achieving Jidoka requires building and improving systems by hand until they are reliable and safe [27]. First, human engineers meticulously build each new line component by hand to exacting standards, then, through incremental Kaizen, steadily simplify its operations. Eventually, after the value added by the line's human operators disappears, the Jidoka mechanism is incorporated into actual production lines. Through the repetition of this process, machinery becomes simpler and less expensive, while maintenance becomes less time-consuming and less costly, enabling the creation of simple, slim, flexible lines that are adaptable to fluctuations in production volume. For Toyota, machines and robots do not think for themselves or evolve on their own. Rather, they adapt as skillful workers transfer their skills and craftsmanship to machines. In other words, craftsmanship is achieved by learning the basic principles of manufacturing through manual work, then applying them on the factory floor to steadily make improvements. This cycle of improvement in both human skills and technologies is the essence of Toyota's Jidoka. At the TPS, human wisdom and ingenuity are indispensable to delivering ever-better cars to customers [27]. Toyota constantly tries to develop human resources who can think independently and implement Kaizen. Most Japanese manufacturing firms adopt the TPS philosophy, and they build their own TPS philosophy. For example, Fujitsu calls its own TPS FPS (Fujitsu Production System), and Omron also calls its own TPS OMPS (Omron Production System).

However, after 2007, the mass retirement of engineers who had accumulated such manufacturing know-how at development and production sites brought about a crisis in the transmission of tacit knowledge skills in most Japanese firms. One factor that has accelerated this trend is the low ratio of young employees, who are expected to lead the next generation, as new hires have been curtailed since the collapse of the bubble economy [9]. As a result, the traditional Monozukuri learning system based on "transmission of skills within organizations" (OJT) has been shaken. One possible response is the use of artificial intelligence (AI). AI machine learning methods include deep learning with neural networks, multiple regression analysis, and decision trees that were used as powerful AI methods until just before the advent of deep learning, random forests, and Bayesian networks [37].

Manufacturing industries in Germany are facing issues similar to those in Japan, including a shrinking, aging work force and difficulties in transferring skills from skilled workers to the next generation [19,21].

Therefore, with limited unique organizational skill transmission and organizational learning systems in Japan after 2007, most Japanese firms are trying to utilize digital technologies such as IoT and AI. For example. Shimane Fujitsu is doing an entire process from assembly and testing to packing on one production line, such as the fully automatic integrated line for printed circuit boards [19]. Humans and machines are working together on the assembly line for PCs. Robots work on fastening screws and attaching stickers. Workers customize each PC according to ID codes given to each model. In this way, the lead time is cut to one-fifth of the time it took under the previous system. It is production based around a conveyor belt, yet each product can be customized. Large-item, small-volume and mixed-flow production is supported by data sharing and manufacturing based on full interaction between humans and machinery that uses IoT technology such as RFID tags. This example shows visions of the future of designing a factory floor where humans, collaborative robots, and autonomous agents form dynamic teams capable of reacting to changing needs in the production environment [5]. The human actors have personally defined roles based on their current skills. However, they can also continue to develop their skills and change their role in the team. Simultaneously, autonomous agents and collaborative robots are able to learn through AI capabilities. Like actor–network theory, all the actors are in continuous interaction by communicating, collaborating, and coordinating their responsibilities, focusing on describing sociotechnical networks and interaction via empirical, evidence-based analyses [5]. Though actor–network theory can help understand how a dynamic human–machine team works and how it evolves over time, to date, no study has examined this notion empirically. Thus, to address this gap, we aim to propose a new model to design sustainable human–machine collaborations.

2.2. Comparison of Manufacturing IT System of Japan and Other Countries

Japanese integrated manufacturing (Monozukuri) is based on factory-level embedded system knowledge, and Japanese Monozukuri capabilities in terms of technological depth and quality processes are well documented [10,38,39]. Yet, the existing IT systems are not well suited for the global expansion of Japanese Monozukuri system capabilities due to the large amounts of embedded knowledge in these systems at the factory level. An Integrated Manufacturing IT System (IMIS) responds to both the known existing needs and the emerging needs (new customer requirements) through the strategic planning of design information [40]. It also identifies the key processes in terms of (1) frontend development; (2) product planning integrating customer needs—expressed or unspoken—and design information; (3) product design visualizing design information; (4) procurement and manufacturing transferring design information through media choices; (5) sales and marketing engaging customers by design information; and (6) maintenance activities managing design information as process routes [40].

However, the implementation of a Global Standard IT System (GSIS) such as CAD and ERP allows firms to immediately adopt the best business processes of top global firms. However, due to the rapid development of IT technologies, all IT systems, without exceptions, keep upgrading their internal capabilities [10,38,39].

In view of such breathtaking speed in technological change, it is unreasonable to overlook global IT standards. Naturally, Japanese firms are more likely to adopt global standard IT systems (e.g., ERP and SCM packages) that go beyond firm-specific IT system development.

In Japan, during the post-World War II period, a historical context of "shared destiny" among people led firms as a whole to own value-added flows in the form of integrated manufacturing work environments [10]. The Japanese style of IT support for IMIS put emphasis on IMIS-centered IT systems and enabled Japanese factories to attain outstanding field-level productivity and flexibility. However, the focus on IMIS did not promote standards that could be shared by both corporate strategic divisions and factory field operations, thus creating relatively weak global system linkages.

On the other hand, the concept of GSIS, with its strong emphasis on the needs of specialized functional segments, is not necessarily compatible with an approach based on IMIS [38]. As current Japanese manufacturing firms focus on sustainable competitiveness, implementing GSIS by sacrificing field-level productivity performance is able to bring worse results.

Fujimoto and Park (2015) highlight the strengths of IMIS and points out the need for GSIS [10]. Specifically, they argue in favor of a Global Integrated Manufacturing IT System (GIMIS) that integrates both IMIS and GSIS. Figure 1 shows an ideal GIMIS, which might be a way to fulfill the dynamic requirements of the emerging IoT and Industry 4.0 and, at the same time, to achieve high levels of intelligent system specifications for IMIS needs, focusing on a comparison of comparative advantage among countries [6,10,38,39]. Internet of Everything (IoE) consists of three layers; (1) ICT system, (2) FA-ICT system, and (3) Factory Automation (FA). Fujimoto (2017) asserts that Western firms (in particular

American firms) are strong at the ICT system level [41]. GAFAs (Google, Amazon, Facebook (Meta), and Apple) are representative firms showing their presence in this ICT system [40]. However, Japanese firms strive to compete with rivals at the level of FA [41].

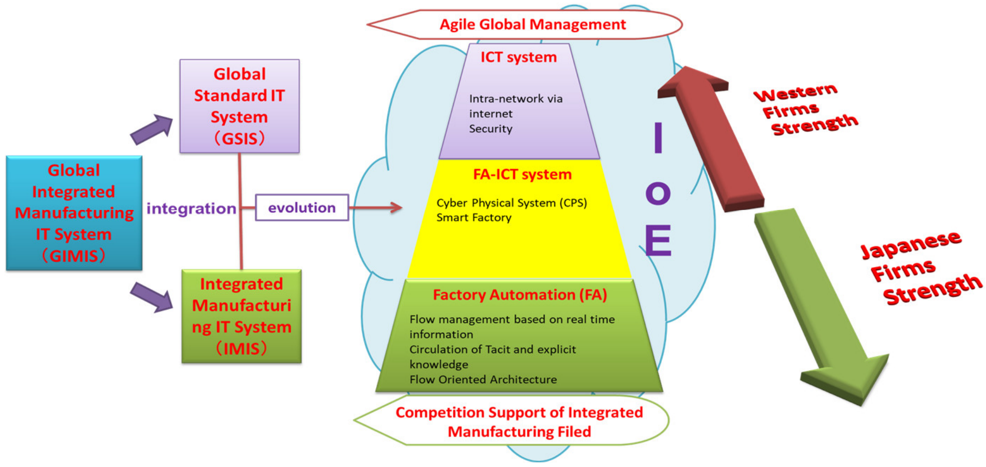

Figure 1. Comparison of Manufacturing IT System of Japanese and Western countries. Source: Adapted from Fujimoto and Park [10].

Furthermore, there have been studies to show the difference in IT utilization among nations [12,14,39,42]. For example, in an advanced comparative study, even implementing the same types of technology, Japanese auto-manufacturers report their product development time fewer than 18 months while American firms require more than 30 months [12,42]. In another study, the American and European firms (Chrysler as an example) adopted 3D CAD three years earlier than Japanese firms, and the actual results show that Japanese firms are still ahead in virtual digital mockup [12,42]. In the late 1990s, most American firms adopted 3D CAD for drafting their 100% component parts, while Japanese counterparts drafted only 49% of their component parts. Although Japanese firms were lagging behind American firms in terms of IT technology adoption, they somehow performed better because their functional specialists are better accustomed to organizational routines for innovative problem-solutions [14,39,42].

These results are a clear indication of the international differences in organizational capability among companies using IT systems such as ERP and CAD. Especially in the midst of an IoT boom, such as smart factories in recent years, there is a gap between the Japanese firms in IT utilization capability. Perhaps when there is a lack of awareness of IoT tools that utilize the existing Monozukuri tacit knowledge, which we define as knowledge seen in the process of building various IT systems, it is likely that they will often fail [43].

Monozukuri of Japan originally had the philosophy of system thinking. As we discussed before, when we look at TPS, it has performed Monozukuri from the customer's point of view. Similarly, the philosophy of Sales, Production, and Stock of Komatsu, a maker of construction machinery in Japan, came from the same spirit of thinking about the integration of production and sales as many Japanese Monozukuri companies. Komatsu's Komtrax system started as a way of remotely monitoring and tracking equipment for the purpose of improving operational efficiency and realized the integration of Sales, Production, and Stock by utilizing DX technologies [44].

This case follows its evolution towards other uses, including demand forecasting for its sales, marketing, and production operations. In order to realize this, many Japanese firms have been conducting the Waigai (Brain Storming technique for creating ideas for Honda) in Obeya (Big Room).

Through a case study, Enomoto (2019) also asserts that amongst Western manufacturers, engineers in the production technology department and technicians in the production line do not directly collaborate [20]. It is normal for technicians to only use it, and even if there is a problem on the production line, figuring out solutions is the job of the production engineer, not the operation manager of the production line. The authority and duties of the company are clearly separated, and mutual infringement is prohibited under the employment contract. On the other hand, at Japanese manufacturers, production engineers in the production engineering department and shop floor technicians collaborate to hold discussions in order to produce better products and process reforms and production equipment layers. Japanese firms compile concrete plans such as improvement of measures against short stoppage by matching and coordination in the mass production preparation stage, and even if they start mass production activities, they propose Kaizen so that the factory site can use the production equipment more efficiently and make better ones. For this reason, Western manufacturers have not succeeded in organizing a team that learns independently and constantly performs Kaizen, which forms the basis of TPS at Toyota Motor Corporation and other Japanese firms.

Thus, we can infer that IT usage patterns among global firms might be different depending on their traditional accumulation in the age of analog.

2.3. Research Model: Deduction, Induction, and Abduction Reasoning

In this article, we consider that there is a difference in the way of using IoT that utilizes Monozukuri's tacit knowledge in Japan's field in preparation for utilizing IoT technologies. Given the relationship between the IoT tool and the existing Monozukuri tacit knowledge, all tools must ultimately contribute to Monozukuri's performance (productivity improvement, high quality, low cost, fast delivery, low defect rate, etc.).

Furthermore, we examine this process in terms of 'deduction, induction, and abduction' reasoning. Around 1901, Peirce began to explain abduction as the first stage of scientific inquiry when brand new ideas were discovered [45]. In comparison to deduction or induction, abduction might seem accidental and instinctive because it is a form of reasoning that activates one's instinct or insight [45,46]. For example, if an agent were to observe that some light was not working, it can hypothesize what is happening in the world to explain why the light was not working.

Thus, Peirce defined abduction as the only method of discovering new facts, among other inferences [45,46]. Although questions have been raised by some logicians on the validity of abductive reasoning, many psychologists have found abduction useful to explain how creativity works, how the controlled and uncontrolled portions of the mind are linked, and the fundamental source of one's own decisions. Borrowing ideas from Aristotle, Peirce examined three basic modes of inference—abduction, deduction, and induction—and also characterized abduction as guessing and as inference to an explanatory hypothesis [45,46]. As shown in Table 1, deduction reasoning has a rule–case–result process, and induction reasoning has a case–result–rule process. However, abduction reasoning has rule–result–case process.

Table 1. Three Types of Decision-Making Methods.

Deduction	Induction	Hypothesis (Abduction)
Rule: All the solutions from this system are right. Case: These solutions are from this system. Result: These solutions are right.	Case: These solutions are [randomly selected] from this system. Result: These solutions are right. Rule: All the solutions from this system are right.	Rule: All the solutions from this system are right. Result: These solutions [oddly] are right. Case: These solutions are from this system.

Relating to the modes of inference in deduction, induction, and abduction, the heuristics concept has been studied, which characterizes abductive cognition [47]. Abductive reasoning has gained increasing interest in many fields of AI research [48]. Its utility was first observed for diagnostic tasks [49,50]. According to Paul (2000) [48], different applications have been suggested including plan recognition [51], text understanding and generation [52], program debugging [53], vision, planning [54], failure [55], user modeling [56,57], case-based reasoning [58,59], and learning [52,60,61].

Abduction, induction, and deduction are strictly related forms of defeasible reasoning, but machine learning research is mainly focused on inductive techniques, leading from specific examples to general rules, with applications to classification, diagnosis, and program synthesis [55]. Though abduction has been used in machine learning, its use was typically an aside technique to be integrated or added on top of the basic inductive scheme. Bergadano et al. (2000) discuss the general relation between abductive and inductive reasoning, showing that they solve different instantiations of the same problem [62]. After they analyzed the specific ways of abduction used in machine learning, uses of abduction in learning have been proved to be effective for their intended purposes [62]. Thus, in terms of the use of digital technologies for problem-solving, deduction, induction, and abduction are closely related to each other.

In this article, we will focus on the case of Japanese companies compared with a German firm and discuss the ideal way of introducing IoT in order to recover Japan's Monozukuri strength. Table 1 describes the three types of decision-making methods, where we focus on the third type, abduction, in the Japanese context.

We also discuss the organizational capability to utilize ideal external technologies in terms of deduction, induction, and abduction inference structures when introducing new IT systems or tools such as IoT. In particular, from the viewpoint of deduction, induction, and abduction, we assume that Japanese companies start from the visualization of the initial induction level and hypothesize that the most successful IT system introduction sequence is for the model to evolve from deduction to abduction. However, based on Fujimoto (2017), we assume that American and German firms start from the visualization of the initial induction level and then evolve into autonomous control at the deduction level [41]. The research model of this paper is shown in Figure 2.

	USA/Germany	Japan
Level 5: Robot–Human Collaboration		Abduction
Level 4: Autonomous control	Deduction	Deduction
Level 3: Prognosis Maintenance Level 2: Error detection level Level 1 Visualization level	Induction	Induction

Figure 2. Research Framework.

3. Case Study

This study conducted an exploratory case study of IoT introduction to Japanese manufacturing firms [63]. We adopted a qualitative approach by conducting three case studies to address our research objectives. As qualitative reasoning has been extensively used in information systems research, a shift of interest has been made in the direction of organizational issues of information systems science [11,64,65]. As such, a case study approach is appropriate for answering questions that are not limited to what (descriptive study) but also how or why (explorative design) a certain phenomenon occurs and for obtaining a first-hand and in-depth understanding of the phenomena [11,63]. Therefore, a case study design was chosen for fulfilling the objectives of this study, given our aim to gain first-hand insights and clarify the utilization of DX technologies in companies in a holistic manner.

In this paper, to examine our research framework, we describe the situation and tasks of the case of IoT introduction of Japanese manufacturing firms and propose the case of

Automotive device firm-D and Healthcare device firm-F as a successful Japanese model in the process. We select these case studies as the initial IoT factory in Japan, fitting our research framework. Then we compare Japanese cases with German firm-B.

We visited each firm and obtained responses from each company regarding smart factory strategy. Specifically, after the factory tour, we conducted semi-structured interviews with senior managers responsible for smart factory strategy at the case firms. Table 2 shows the overview of case firms. The site visiting and the interviews were undertaken from 2017 to 2022, and each lasted 3 to 4 hours. In addition, the information was supplemented based on publicly available information from companies and secondary sources. Furthermore, based on the information obtained therein, an additional discussion was conducted through email to confirm, supplement, elaborate, and verify the interview data and our interpretations.

Table 2. Overview of the Case Firms.

Type	Firm-D	Firm-F	Firm-B
Nationality	Japan	Japan	Germany
Production products	Injectors	Endoscopes and related parts	Pharmaceutical products
Target plant Description	Automotive device plants	Healthcare device plants	Pharmaceutical production plants

3.1. Firm D Case

Firm D has many factories worldwide, including domestic factories in Japan. It develops and produces mainly automobile components such as injectors. Firm D's main domestic plant (Factory Z) began its operations in 1998. As of July 2018, there were 1735 employees, including 724 temporary employees. Firm D's European oversea factory has 7000 employees. In the case of high-performance, high-precision, and small-sized components such as injectors, all of them are manufactured domestically and transported worldwide. These products are small and easy to carry and, therefore, high in terms of transportation efficiency. Thus, it is produced by a domestic factory.

Recently even if it is becoming harder to find people due to a shrinking, aging work force, at present, 33% of workers are temporary workers, but since it is a lot, it plans to reduce it to 20%. The wages of temporary workers are also increasing. As it is developing materials in an integrated vertical system, they have begun to consider the utilization of IoT technologies. Recently, however, the question of how to do something that is not an integration has become an issue. Human resource development is the foundation of manufacturing, and it tries to continuously improve its field capabilities.

Since the 1980s, it has been working on the computerization of factories. However, since the government decided to promote globalization, the trend toward information technology has slowed down. Since then, it has been recovering recently. Its basic idea for introducing IoT is to develop its core strengths. Specifically, it is working on "JIT of information" and "personalization of Andon (individual Andon)". The latter makes it possible for a specific person to obtain the information when someone needs it. Therefore, it wants IoT to be able to tell them things it had not noticed before. People are an important factor in using IoT. IoT and AI will be no better if it does not input quality information in a good field. In particular, there are many challenges in the field overseas, so it is important to practice excellent methods in the field in Japan, let the system learn, and expand globally.

As Firm D has various businesses, it is difficult to suddenly create a system that can be used in common among wafer factories, air conditioner factories, and cylinder factories, so it decided for each factory to try and create a system. In this case, we show its efforts in the field of factory chains.

In reality, however, the plan is to extend IoT to include engineering chains, supply chains, and market chains. Big data and features must be created according to the features of the processing equipment. It is stratified in order to consider the content connected by IoT. The objective is to improve the competitiveness of each business and region. For each business, product, factory/person, processing/facility, category, and features, the basic policy of manufacturing to win and necessary IoT services are listed in more detail, and a star list is made for each product business. It is very hard work, but it is working well because it is necessary to improve its competitiveness. In addition, Firm D is working on knowledge and wisdom, work style reform, management KPIs, and business continuity planning (BCP) to improve the manufacturing capabilities of the entire company.

In considering the use of connected content, it focuses on both (1) inductive and (2) deductive solutions. The level of utilization is divided into five levels. Inductive solutions are the use of results, from visualizing the present (trend changes based on factory information) to visualizing the future (Big data analytics, AI, and machine learning). Next, it wants to proceed to the deductive solution, that is, the utilization of factors. It advances from formal intelligence to intelligence. Once the logic is understood, the process of immediate improvement is created. After all, people will not move unless they are convinced. Finally, the fifth level of utilization (abduction level) also assumes that the cause of the problem can be eliminated; that is, the operation through human-robot collaboration can be improved. The idea is that if it can get to that point, it is okay to remove the sensor from the process.

As of 2018, its goal is to proceed to 18 manufacturing sites in Japan up to Level 3. As long-term goals, it plans to achieve Level 5 by 2030. Currently, this approach is limited to the factory, but each division has different positions, so it is necessary to introduce it in accordance with each division. It is important to develop the good points of each base.

Specifically, the injector machining cycle time is as fast as 10 s. Since the factory is rich in facilities, the key is how well the facilities are used. The Z-Plant of D-firm is suitable for introducing IoT systems for facilities. JIT of information and efforts of individuals are carried out. The common rail assembly is carried out overseas, but The Z factory does not have the same overseas factories.

Firm D is thinking about IoT systems with overseas factories in the future. By visualizing workflow lines, it wants to speed up training for overseas workers. It also tries to use open source when it builds the system so that it can build it as freely as it can. Modules are divided, designed, and combined by function. The plant management system, the analysis system, and the production preparation management system are all designed to follow the evolution of the field. By implementing Firm D's IoT, global standard specifications (equipment specifications) will be set. It is designed so that any facility can be used as long as the middleware is properly inserted.

Recently, Firm D also has edge computing and cloud functions in-house. Since all vibrations and sounds are converted into heat energy in the rubber, the firm has developed a sensor that can detect the change in heat quantity, and the domestic factory is using this technology. In facility management, the change point is more important than the absolute amount of change. Therefore, rather than the absolute value, it is useful to use a sensor that can integrate various factors into the change of thermal energy and detect the change in detail. The sensor is manufactured in-house, and the sensor system has a good reputation and is sold externally.

There is a Global Factory IoT conference every 3 months. About 100 people from each base and region participate in this program. It was held eight times from 2016 to 2018. The argument here is that the user interface is very important. In particular, it is very important to use it in overseas factories. In order to make the UI easy to use, the firm has been working on specifications with overseas members since the beginning of development.

As of 2018, in order to respond to changes in customer requirements, the process facility change section, model drawing change section, cost fluctuation, business profit, process change effect, and check item list are managed by one person for each item, with personnel from sales, planning, design, and engineering. The goal of using IoT in the future is to allow one person to handle all of these design changes.

Injectors are very sophisticated and difficult because they require pressure resistance, heat resistance, fuel spreading, fuel sharpening, and millisecond control. There are two types, solenoid type, and piezoelectric type. The piezoelectric system enables control in a shorter time. It is difficult to measure whether the fuel is blown correctly. This measurement is essential. The injector consists of 40 parts, each with an intersection of ± 1 micron and a stacking tolerance of ± 1 micron. Since it is difficult to manufacture as designed, it is important to keep the whole product within the tolerance when finally assembled. Without considering how to assemble the whole parts, it is impossible to control within the tolerance. The combination is difficult to solve deductively, so the firm has to find the best way to combine the products as a whole through many experiments. The product quality is improved by piling up the parts in a fine manner and piling up each part in micron units. As a result, it is difficult for other companies to copy it. Firm D is also doing something special about measuring the intersection of parts. The equipment for this purpose is also manufactured in-house. The cutting tools used to be bought from a Germ firm B, but now they are made in-house. When they bought equipment from a Germ firm B, they did not know the actual details of the recipe, so they had to start from scratch. In addition, the cutting tools used in Vietnam, Thailand, and Mexico are manufactured in-house.

The IoT unit is in the production engineering department. There are about 60 people in total. The IoT unit of Firm D started with four people. Mr. K has been at Firm D for about 22 years, but since he has been a production engineer in the manufacturing department for the first 18 years or so, he knows manufacturing well. In this way, it seems to be a good idea to have someone in the manufacturing department who knows what is going on in the field involved in the adoption of production technology and IoT. After all, it is important for the firm to have a desire to improve because such attitudes drive continuous improvement.

3.2. Firm F Case

Firm F, one of Fujifilm group firms, was established in 2005 through the integration of five companies under the F Group's manufacturing equipment firms. The company manufactures printing and imaging equipment (mainly medical equipment) and is the core manufacturing company under F Group's equipment business. F group has been steadily expanding its business, and in 2016, Firm F, a manufacturer in the field of optical devices, integrated its endoscope production functions through a company split and began to manufacture endoscope equipment.

The new smart factory, which was constructed in the S Plant of Firm F, began full-scale operation in October 2019 as a new production base for endoscopes. The new smart factory has been producing endoscopes and related parts. This new smart factory is a smart factory that has significantly increased production efficiency by using IoT and AI and is aimed at doubling the production capacity of endoscopes.

An information system Manager of Firm F, the project leader for the start-up of this plant, said that since a new factory needs to be built, they incorporated various ideas to allow flexible layout changes, and they communicate wirelessly, and he said automatic conveyors (AGVs), which carry parts and products, were controlled by radio.

Generally speaking, the image of a factory is that large equipment, facilities, and robots are used to automatically process and assemble products, and workers are involved in these processes in an auxiliary manner. When it comes to IoT and AI-powered smart factories, there's often a vision to take this automation even further and make it unmanned.

The new smart factory, which began operations in October 2019, is the F Group's most advanced smart factory, but its contents differ slightly from the image of a smart factory described above. A manager of Firm F explained that they incorporated measures to make production more efficient and smarter for this new smart factory. It is a smart factory where people really play a leading role.

The smart factory's human-centered design is largely due to the characteristics of the endoscope final assembly process at this new plant. The endoscope is not a mass-produced product but a high-mix, low-volume product whose specifications are flexibly changed to meet customer requirements. As the work depends on delicate technology, such as using microscopes to attach tiny lenses, most of the production process is performed manually. Thus, the new smart factory has introduced an original process support system to each worker's workstation in order to record the work contents of the workers and to enable accurate work instructions. Such work demands, in turn, facilitate the creation and digitization of Device History Records (DHR) required for instruction to workers and manufacturing of medical devices.

Many IoT-enabled smart factories rely on data collected from machines and equipment such as sensors. At the new smart factory in Firm F, however, it is required to collect production data from people. Sensing by IoT devices and beacons used by workers follow the policy of collecting production-related data from people.

A large number of skilled workers work at this new smart factory, which produces endoscopes that require delicate work. However, passing on the skills of these skilled workers and developing new human resources is an important mission for this new smart factory, which is a smart factory where people play a leading role. Human resource development is conducted at a training center in the factory, and a skill certification system has been established to create an environment where more advanced skills can be acquired. Therefore, a manager of Firm F indicated that it is important to set up a system to nurture new employees to the same level of work as skilled workers.

The image inspection process for endoscopes is time-consuming, even for experts, because it requires careful checking of dust, stains, and noise generated as image output.

The new factory adopted AI technology in the image inspection process of endoscopes after final assembly. The video inspection process is automated, reducing the manpower required for inspection. Regarding the production process of endoscopes, which is mainly made by people, it is not realistic to continue to assign skilled workers to all processes in view of the decrease in the labor force in the future. Therefore, Firm F decided to automate the inspection process so that skilled workers could work on more difficult, value-added assembly processes. In addition to reducing inspection work, this automation has also enabled the quantification of judgment criteria.

3.3. Comparison with German Firm B

Firm-B (Bayer AG) is a German global pharmaceutical and chemical company with over 350 subsidiaries and more than 100 manufacturing facilities in 150 countries. Bayer is a global enterprise with core competencies in the life science fields of health care and nutrition. The Bayer Group's three major subsidiaries are: Bayer HealthCare, Bayer Crop Science, and Bayer Material Science. They sell over 5000 products, including cold medicine, adult disease, as well as diagnostic devices, animal vaccines, herbicides, insecticides, rubber, and plasmatic parts.

Since its inception as a dye manufacturing company, the firm has grown steadily and into Germany's first comprehensive pharmaceutical/chemical group. However, after a huge crisis in the 2000s, Bayer reduced its overall size by 20%, focusing on future-oriented industries such as healthcare, lingerie, and advanced materials. In 2004, Bayer chose to "position pharmaceuticals as a medium-sized enterprise" and to focus its US pharmaceutical business on specialty and biotech products for specialist physicians.

In fiscal 2021, the Group employed around 100,000 people and had sales of EUR 44.1 billion. R&D expenses before special items amounted to EUR 5.3 billion.

Recently, Bayer announced that it is strengthening the production network of its pharmaceutical division to ensure sustainable competitiveness and support the transformation of its pharmaceutical business based on breakthrough innovation delivering long-term, sustainable business growth. By investing in new technologies, automation, and digitalization, Bayer will implement a comprehensive program to substantially upscale its pharmaceutical manufacturing. Over the next three years, Bayer will invest around EUR two billion into its manufacturing and supply chain capabilities.

Germany will remain an important strategic manufacturing location for the company. Recently, Bayer AG has celebrated the topping-out of its new pharmaceutical facility in Leverkusen, Germany, which is one of the most modern pharmaceutical production plants in the world. It is part of a billion-euro investment program that Bayer is implementing to strengthen its pharmaceutical production network and the company's in-house innovation power. The plant will be at the heart of the new global Center of Excellence for the production of solid pharmaceutical products at the Leverkusen site. According to the company, it will not only set standards for efficiency, quality, supply security, and sustainability but will also leverage the advantages of digitalization in a learning factory to build an environment in which data streams are analyzed using AI in order to derive action recommendations.

However, the flow of IoT technology in Bayer, such as other American and German firms, is pursuing IoT with the aim of Level 1 to Level 4 of our research framework. All the manufacturing processes are automated from manufacturing to final packaging. A production manager explained they seek to automate all the processes completely and link to all supply chains through ERP systems and external logistic systems. Therefore, the role of a mechanical engineer is more crucial than skillful workers, different from Japanese firms. In other words, the IoT promotion strategy is centered on IoT systems and mechanical engineers who are capable of managing all manufacturing processed automatically.

3.4. Five-Level Framework for Utilizing IoT or AI

First, the framework of this paper suggested that there are five levels in terms of utilizing IoT. The idea of things includes induction, deduction, and abduction. Especially, abduction is not an area of machines or robots because it recalls the hypothesis suddenly when the accident is abrupt. In other words, it is performed out of the human reasoning structure. Even if firms collect big data at the same Monozukuri site, they should think about whether they can use it effectively by abduction. In other words, a person should be a subject, have a hypothesis about the logic behind it, and give an answer to the results presented to IoT/AI.

Second, as discussed in the introduction, Japanese companies have built a process capability to collect and analyze various data from analog facilities, even with the transfer of big data due to the introduction of the latest IoT, because of the Monozukuri strategy. Because it has such characteristics, it recognizes that it is important to interconnect with digital data through new IoT technology.

Third, the trend of IoT technology in the United States and Germany is pursuing IoT with the aim of Level 1 to Level 4, as presented in this paper. However, in the case of Japanese companies D and F, the ultimate goal is Level 5. That is, an IoT promotion strategy that is centered on skillful human beings.

Fourth, no matter how good an IoT or AI tool is, the usage of these means is determined by the human being. It can be said that this is because of the principle of solving all the problems based on the logic and the theory of the tacit knowledge of the Monozukuri field that has been accumulated so far in Japanese companies. As shown in the Toyota production method, the strengths of Japanese companies are to solve the problem by repeating the fundamental "5 why questions (why -> why -> why - > why -> why - > solution)".

Fifth, Japanese companies that successfully utilize IoT can be characterized by their ability to go back to the fundamental problem of the phenomenon and eliminate the root cause of the problem, that is, Level 5.

4. Discussion and Contributions

With three types of decision-making methods, this research tries to analyze an exploratory analysis through a comparison of the utilization pattern of the digital technology of American, German, and Japanese firms and shows different ways in which the DX technologies are utilized in these three countries.

4.1. Theoretical Contribution

First, we present a research framework that is based on three types of decision-making for problem-solving: (1) deduction, (2) induction, and (3) abduction. Though abduction, induction, and deduction are strictly related forms of defeasible reasoning [55,62], traditional machine learning research is mainly focused on inductive techniques. Though abduction was used in machine learning, its use was limited [47,48,62]. Furthermore, these reasoning methods are not used for the analysis of management decision-making. We first used these three types of decision-making for problem-solving and the human–machine collaborations in the area of manufacturing [5]. In particular, to analyze international comparison, we showed different evolutionary pathways in each nation's firms. A research framework with empirical studies is applicable to not only the use of digital technologies but also problem-solving of management and the evolution of innovation in general. Thus, this article extends the traditional machine learning application of three types of reasoning methods into managerial decision-making.

Furthermore, based on our findings, we propose several propositions concerning the relationship between the degree of automation and the firm's reliance on tacit knowledge.

As discussed before, to manage the labor shortage, current Japanese SMEs have decided to introduce many robots to automate their factories [9,43]. When comparing the cost-efficiency of machines vis-à-vis humans, there are competing views on human–machine collaboration. Historically Japanese firms have held a philosophy that humans learn a body of knowledge over time and increase their proficiency level by repeating the same task over a series of trials, ending up fostering multi-skilled workers [43]. At the factory level, as previous routines become patterned as a practice is repeated, Japanese multi-skilled workers evolved previous routines and expanded their routines according to education and continuous learning. Although the introduction of novel technology (such as robots utilizing DX technologies) or transfer of previous routines to different organizational contexts can stimulate dynamic organizational learning, we think it is difficult for current robotics to work like multi-skilled workers [43,66]. In other words, robots are not replacing workers, but instead complement them.

In this article, we compared the national difference of suitable human–machine collaborations from the dependence degree of tacit Knowledge at the factory level. While studies have investigated how robotics affect the improvement of productivity, less work has looked at the tacit knowledge differences in the use of DX technologies such as autonomous machines. Park (2020) shows there is an important gap in terms of addressing how to decide the optimal time to switch from a human to a machine-centered manufacturing line or choosing to keep a human-centric manufacturing line [43]. Though new technologies such as autonomous machines and AI allow organizations to automate an increasing number of routine tasks in the changing world of work, improving work whilst being unskilled is non-routine and therefore harder to automate. For example, when Park (2020) compared Japan factory (OH HQ) and China (OHC) and Vietnam (OHV) factory in Omron, the Japanese factory with lots of multi-skilled workers and high human costs had the most sophisticated automation machine [43]. As such, the firm's degree of automation can be affected by the tacit knowledge of multi-skilled workers and labor costs.

Figure 3 presents the different types in response to Degree of Automation (DA) and Dependence Degree of Tacit Knowledge (DDTC) as the two axes. Based on our findings, we suggest propositions along the two axes.

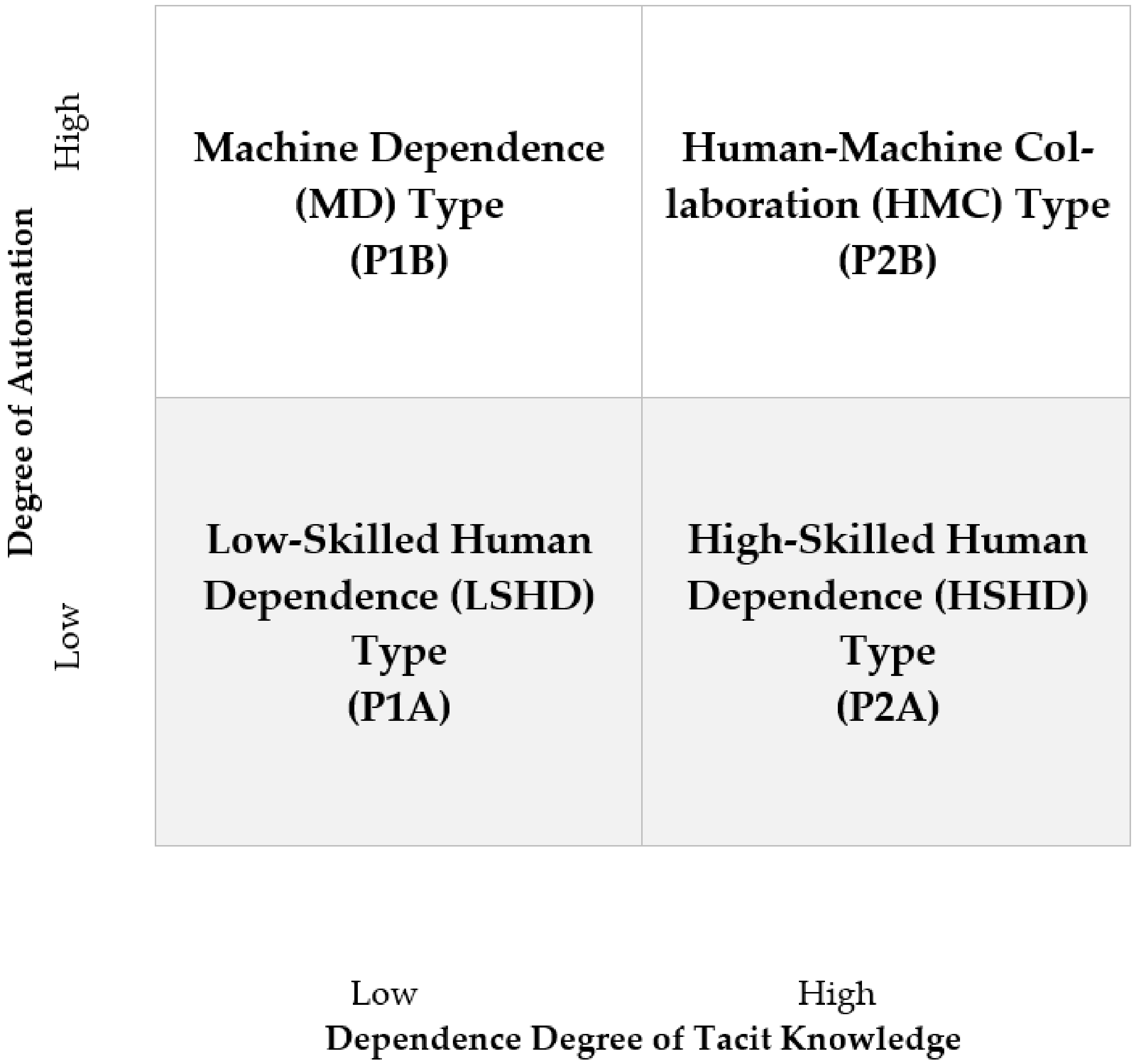

Figure 3. Types in response to Degree of Automation (DA) and Dependence Degree of Tacit Knowledge (DDTC).

The first and second patterns are Low-Skilled Human Dependence (LSHD) Type (P1A) and Machine Dependence (MD) Type (P1B), which represent the use patterns of DX technologies with a low dependence degree of tacit knowledge. In the situation of a low dependence degree of tacit knowledge, the automation level of firms has an influence on the performance of DX technologies.

Therefore, we posit:

Proposition 1:

In the situation of a low dependence degree of tacit knowledge, Machine Dependence (MD) Type is more likely to exhibit higher performance than the Low-Skilled Human Dependence (LSHD) Type (P1A).

The third and fourth patterns are the High-Skilled Human Dependence (HSHD) Type and Human–Machine Collaboration (HMC) Type, which refer to firms that are highly dependent on tacit knowledge. As shown in the case study of Japanese firms, they adopted human–machine collaboration as a final goal of DX technologies use, contrary to the German firm. However, in the case of a low degree of DX technologies among Japanese firms, lots of firms rely on the human skills of multi-skilled workers. Especially most SMEs are applicable.

Thus, as proposed above, we posit:

Proposition 2:

The Human–Machine Collaboration (HMC) Type (P2B) is higher performing than the High-Skilled Human Dependence (HSHD) Type (P2A).

Second, we suggest the evolution stage of smart factories based on case studies; Level 1 (visualization level), Level 2 (error detection level), Level 3 (prognosis maintenance), Level 4 (autonomous control), and Level 5 (robot–human collaboration). Furthermore, we connect these five stages to three types of decision-making for problem-solving: (1) deduction, (2) induction, and (3) abduction. This framework can be used not only for the evolution of digital technologies at a firm level or an industry level but also at a national level.

Third, our study is in line with previous research concerning relations between product architecture and IoT utilization capability. Product architecture is "the overall mapping to envision and identify product functions and distributes them through common elements, essential processes and critical interfaces through which vital information and value creation opportunities are shared and realized" [12–14,38,39,42,67,68], and this product architecture affects innovation strategies of firms in the era of DX [40]. As all firms must consider the fitness between this architecture and innovation strategies, it is necessary to discuss the implication of these factors for the business architecture.

As discussed before, the adoption of external IT systems often implies that firm-specific contexts and organizational identity are neglected [10,38]. In addition, even the best systems become outdated and rigid over time, hence becoming less able to respond flexibly and quickly to dynamic and ever-changing needs. The only way to remedy these shortcomings is to consider user initiatives and develop a unique system that reflects firm-specific identity-based requirements. For the sustainable delivery of outstanding products that exceed customer requirements, it is crucial to build an IT system that ensures the integration of product development processes and organizational capabilities. The essence of this winning strategy is a firm's ambidextrousness, which highlights strengths and complements weaknesses. This new range of organizational capabilities thrives on integral architecture for the integrated manufacturing of complex products (e.g., automobiles and medical equipment), which is a typical trait of outstanding Japanese manufacturing firms; yet, it is also capable of adopting an open modular architecture for consumer products (e.g., electronics), which requires a large number of suppliers with limited manufacturing capabilities. In this way, they can attain long-term global competitiveness by penetrating both emerging and advanced markets. An ambidextrous strategy uses both integrated manufacturing IT for integral architecture products and global standard IT for global modular products. In other words, human–machine collaboration study can be extended to a GIMIS concept that integrates IMIS and GSIS [10,38,39].

As discussed earlier, if the utilization pattern of digital technologies is different among countries, industries, and firms, firms that utilize DX should examine whether there is a fit between the utilization of new digital technology and the organization's capability of DX technology.

In particular, for holistic DX utilization beyond DX at the factory level, it is more important to integrate a database in introducing an IT system. Without integration among databases, the introduction of IT may result in a worthless investment. For example, 3D CAD-CAE promises a reduction in development time through front loading and smaller design changes under the right kind of organizational capabilities [12,39,42]. Thus, global firms should admit differences in organizational capabilities to utilize IT systems and conduct strategic decision-making for the utilization of DX that best suits their own capabilities.

4.2. Managerial Contribution

First, this study presented the benchmark tool to assess the utilization capability of digital technologies. This research framework is useful for firms to classify, assess and evaluate the stage of a smart factory. Most firms remain in Level 1 (visualization level) or Level 2 (error detection level). However, like the firms featured in this case study, global firms with high utilization capabilities of digital technologies seek to reach Level 3 (prognosis maintenance), Level 4 (autonomous control), and Level 5 (robot–human collaboration). This type of DX use might be different according to the focal firm's historical background and cultural context. Most Japanese firms have built their distinctive capabilities through raising skillful workers set apart from those from other countries. In that case, to use this high-skilled human capital, they should consider a uniquely tailored design of DX technologies. However, most American and German firms can target Level 4 (autonomous control).

Second, case study findings also suggest the road map for the future strategic direction of the adoption of DX technologies. In identifying the current stage of a smart factory, each firm could select a future strategic direction for the adoption of suitable DX technologies.

Third, this study suggests the importance of training data scientists for DX utilization. Computers do not automatically learn and become smarter. Instead, people play a large role in calibrating DX, including modeling how the human brain actually learns and basing their design of machine learning based on the human learning mechanism. A machine learning system with the wrong data runs the risk of Garbage In and Garbage Out. Hence, feedback control mechanisms should also be established to prevent misuse and falsification of data. Therefore, the training of data scientists and systems architects is necessary. For example, recently, Kaggle and other systems have become popular. This allows companies to train data scientists and systems architects. Founded in 2010 in the United States, Kaggle is a predictive modeling and analysis method-related platform, and it allows companies and researchers from around the world to submit data and statisticians and data analysts to compete for optimal models. The crowdsourcing approach to modeling is attributed to the myriad of strategies that can be applied to any predictive modeling challenge. Kaggle has a section called Kernels, where data scientists publish their methods. When comparing these methods, AI-powered machine learning systems are more like art or craftsmanship [37]. In this scheme, although the same dataset is used, participants' performance varies greatly depending on the processing of the data and the model used. The development of human resources capable of making the most of the data in this way is an urgent issue.

Finally, when we consider sustainable human–machine collaborations, feedback control also matters. In the digital world, feedback effects, economies of scale, and network externalities are at work [37,69]. The feedback effect is related to the scale and network effects, but it occurs when the computer system uses the feedback data for learning. If one enters a wrong word in Google's search field, it will automatically correct it and suggest the correct spelling. However, Google is also improving its spell-checker with user feedback. Watson, IBM's AI, is becoming more accurate at detecting specific cancers as the number of diagnoses increases. The feedback effect is that as the most popular products and services obtain more data, so they improve more. Accordingly, innovation in the digital age depends not on ideas but on how much feedback data can be collected. Thus, in the age of data-driven innovation, the development of data scientists (system architects) and the control of feedback between machines and humans will become increasingly important.

5. Conclusions

In this paper, we discussed the difference in decision-making models to utilize ideal external technologies in terms of deduction, induction, and abduction inference structures when introducing new IT systems or tools such as IoT. To this end, we presented the five levels of IoT adoption: (1) visualization level, (2) error detection level, (3) predictive(prognosis) maintenance, (4) autonomous control, and (5) robot–human collaboration level.

Significantly, through our case study, we find that Japanese firms' decision-making approach began from visualization at the initial induction level. Subsequently, their decision-making evolved into deduction—abduction when introducing the most successful IT system. The current IoT promotion in the United States and Germany is aimed at the unmanned smart factory aiming at the fourth stage of autonomous control, but the direction of Japan is based on the tacit knowledge of the strong Monozukuri field. In other words, it is characterized by the level of elimination of fundamental problems in human abduction as an ideal level.

Using exploratory case studies, we examined three representative firms which adopted a smart factory strategy. For the purpose of this article, we chose to conduct an in-depth analysis of a nonrandom sample of firms. For generalizability of results, future studies can design reliable survey instruments or experiments to examine the sustainable human–machine collaborations in DX technologies adoption [5,43]. A bigger scale of empirical studies may provide rich and valuable insights into the dynamic nature of sustainable human–machine collaborations. In the future, cross-national comparative studies beyond Japan and Germany will be important for generalizing our findings which are limited to the Japanese and German contexts.

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