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RESEARCH ARTICLE

Unveiling Key Drivers of Industry 4.0 Adaptation in CKD Automotive Manufacturing Companies: Evidence From Asia and South America

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ABSTRACT The paper investigates the drivers of Industry 4.0 adaptation in the CKD automotive industry. The methodology is based on a cross-sectional empirical study, where the samples were drawn using simple random sampling. Four hypotheses were developed, and the data were collected using an online survey and a standardised questionnaire. Survey responses were received from white-collar employees at a CKD automotive manufacturer encompassing multiple CKD plants in Asia and South America. One hundred fifty survey responses were received and next analysed using Structural Equation Modelling (SEM) in SmartPLS software. Based on the findings, three drivers, namely, business competitiveness, customer satisfaction, and operational improvement, positively affect the Industry 4.0 adaptation in CKD manufacturing companies. However, the financial benefit factor does not affect the adaptation of Industry 4.0 in manufacturing industries. This study contributes to the existing knowledge in understanding the drivers for Industry 4.0 adaptation. In addition, these findings might aid the practitioners and government in tailoring the policy related to Industry 4.0 in CKD automotive manufacturing industries.

INDEX TERMS Industry 4.0, completely knocked down, automotive industry, business competitiveness, customer satisfaction, operational improvement, structural equation modelling.

I. INTRODUCTION

Industry 4.0 (I4.0) is a transformational trend that integrates technological concepts. The key role of I4.0 is to assist the industry in achieving higher efficiency by maximizing output while using the least number of resources by collaborating with the latest manufacturing technologies [1], [2]. I4.0 was first announced at the Hannover Fair, Germany, in 2011 as one of the German strategic initiatives to take the leading role in the industrial sectors [3], [4]. This approach has caught the attention, followed, and been accepted by many countries worldwide [1]. Since its inception, I4.0 has significantly impacted the manufacturing industry, which can be seen in the improvement of operations management and decision-making processes in the business. The integration of digital manufacturing is the root of I4.0, which aims to speed up decision-making and boost production efficiency and flexibility [5], [6], [7].

I4.0 has garnered significant global attention, capturing the interest of both industries and academics, intrigued by its transformative potential [8]. Undoubtedly, an adaptation of I4.0 has a profound impact on financial outcomes, operational enhancements, strategic transformations, and customer satisfaction levels of products [9]. Numerous large-scale industries have made substantial investments in IoT (Internet of Things) and CPS (Cyber-Physical Systems) projects, driven by an escalating interest to ensure long-term competitiveness in anticipation of forthcoming changes [10].

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Prominent companies such as Siemens, Hitachi, Bosch, and numerous others, have exemplified this trend. Their investments enabled them to adapt swiftly to rapidly changing environmental conditions, including shorter product lifecycles, increased product diversity, and evolving customer expectations [11].

Despite the increased pressure and other reasons that may impede automotive manufacturers from implementing I4.0, limited empirical research has been conducted on the phenomenon of the adaptation drivers of I4.0, specifically among Completely Knocked Down (CKD) automotive manufacturers. As proposed by Hermann et al. [12], research on I4.0 could be further validated in multiple case studies covering different types of processes and industries. In contrast to large-scale operations, CKD automotive manufacturing operates within a distinct framework, marked by different contextual elements. For instance, research has demonstrated the significance of localization and regional factors [12], the complexities of component sourcing and logistics [13], the need for production line flexibility [14], and labour considerations. Additionally, most academics are focused on the technological parts of I4.0, while the organizational and administrative aspects of I4.0 are still lacking [15], [16]. Consequently, managers face challenges in acquiring comprehensive views and understanding of the drivers of I4.0, leading practitioners to seek guidance on accelerating the implementation [12].

This study is limited to CKD automotive manufacturers, thus generally attempting to address a research gap in favour of understanding the drivers of I4.0 adaptation. In addition, this research aims to provide beneficial information to be used as guiding material in the research activities related to I4.0 adaptation. Specifically, this study is expected to give significant debatable points that can enlarge and support the literature review on the drivers of I4.0 adaptation. This research recognizes the drivers of I4.0 adaptation in the automotive field. The results will guide the companies in the I4.0 transformation by assisting the manufacturer to continue increasing their production output and model complexity. Additionally, the study also provides evidence of the factors that potentially influence the adaptation of I4.0. Yet, the factors or drivers must be understood before I4.0 is adapted to the industry. Accordingly, the study provides guidance and assistance to the industry's management in strategic planning as an approach to initiate the transformation towards I4.0 technological adaptation. The empirical evidence on the drivers of I4.0 adaptation among the industries would be valuable to all stakeholders, such as policymakers and practitioners, in realizing the objective of the I4.0 policy.

II. LITERATURE REVIEW

A. RELATED THEORY

This research is grounded on the principles of the Dynamic Capabilities Theory, which emphasizes the continuous evolution of a firm's operating environment. According to this theory, innovation is crucial for a company's progression, and all innovations must be evaluated within the same hypothetical inertial frame of reference as they lead to significant changes [17]. Dynamic capabilities are the company's ongoing, systematic and high-level routines that aim to improve its operations and thereby generate profits for the company. Hence, they are more successful in the present and more adaptable to the future environment [18]. This demonstrates that the manufacturer must use the drivers of I4.0 as dynamic capabilities to improve long-term success. This example confirms the importance of this study, knowing that the drivers have a significant impact on company performance.

B. ADAPTATION OF INDUSTRY 4.0

Several conceptual and empirical studies were identified and used to construct the research framework. This section discusses a list of adaptations of each pillar towards Industry 4.0 from the information technology point of view.

1) CLOUD COMPUTING

Cloud computing is a digital technology that uses the internet to deliver computer system resources such as servers, storage, databases, networking, and intelligence [19]. It is a model that enables the real-time leasing of computer resources with minimum supplier interaction [20]. According to Leitão et al. [21], the cloud employs remote internet servers to store, manage, and process data on a personal computer instead of using a local server. This technology enables rapid innovation and facilitates the utilization of adaptive resources. Consequently, cloud users gain on-demand access to an extensive pool of virtually limitless cloud resources [22]. Cloud computing also improves scalability and responsiveness while providing financial gain [20]. Cloud computing has been investigated to be used in various sectors. Helo et al. [23] introduced a cloud-based production scheduling solution for sheet metal fabrication. This innovative system incorporates a genetic algorithm to assist firms in enhancing their operational efficiency and optimizing resource utilization. By leveraging advanced communication technology, this solution enables the seamless transfer of up-to-date information among equipment, production lines, and other stakeholders within the supply chains.

2) INTERNET OF THINGS (IoT)

Internet of Things (IoT) is a critical component of I4.0 and is widely used in industrial and service industries to monitor production processes [24]. With the target to increase performance, this technology allows new and inventive production options by using the capacity to gather and exchange data with internet-connected machines and devices [25]. The advancement of smart devices, mobile networks, and computer technology has revolutionized the concept of IoT, which is set to transform every part of our lives [26]. This enables access to large amounts of user data to generate insights, train task-specific machine learning models, and ultimately deliver high-quality smart services. IoT has several advantages, including information continuity and transparency, ensuring that items and information can be tracked without risk [27]. In the manufacturing world, the IoT fosters a new paradigm [28]. Chow et al. [29] conducted a study highlighting the notable benefits of utilizing radio-frequency identification device (RFID) technology in the automotive industry. This technology employs radio waves to identify objects. An example of RFID implementation was observed in Volvo Truck, which employed an RFID system to enhance operational transparency. RFID technology integration is a crucial enabler for advancements, particularly in traceability. Consequently, it aids manufacturers in minimizing information gaps within the product's information loops. [30].

3) CYBERSECURITY

The industrial communication network is growing and becoming more interconnected, and digital security has become a vital feature in the industrial environment that should not be overlooked [31]. It has become more complex as it includes smart devices and advanced settings, which cannot be protected through traditional cybersecurity measures. The transition to I4.0 requires considerable data collection and processing activities. As a result, data storage and transmission process security became critical for a business [32]. Cloud technologies, computers, robotics, and automated systems must be safe. Certain precautions are required for the security of data export technology, privacy rules, standardization of communication protocols and personal permissions for information sharing [33]. Response to cyber incidents and essential operations recovery should be organized to avoid the consequences of these disorders [34]. It ensures organizational recovery, end-user training, network security, and information security. User account controls, firewalls, intrusion detection systems, and vulnerability scanners' penetration examinations are examples of other preventive measures [33].

4) HORIZONTAL AND VERTICAL INTEGRATION

System integration occurs via several vertical, corporate, and horizontal value chains [35]. As a result, end-to-end digital integration will be possible across the whole value chain. Three factors must be addressed for effective I4.0 adaptation; horizontal integration via value chains, vertical integration, and production or service system networking from end-to-end engineering of the complete value chain [36]. Vertical integration entails the intelligent cross-linking and digitization of business units at various hierarchical levels. As a result, vertical integration enables a highly adaptable transition to a smart factory. It facilitates reasonable profit margins in manufacturing small batch sizes and more customized items. Smart machines, for example, can create a self-contained ecosystem, which may be dynamically subordinated to influence the production of a wide range of products and enormous volumes of data [36], [37]. The data are then processed to enhance the efficiency of the manufacturing process. In contrast, horizontal integration produces an overall value between firms and normally involves product life cycle optimization, such as integrating information systems, smart financial management, and material flow [33]. Real-time data sharing, resource allocation productivity, integrated business units, and precise planning are possible with horizontal and vertical integration. Both horizontal and vertical integration can succeed with the right supporting technologies, product design, maintenance, and recycling systems [36].

5) AUGMENTED REALITY

Augmented reality (AR) is a computer-aided tool to reflect a real-world environment [38], [39]. In other words, virtual information may be integrated with real-world pictures to improve realism by adding dimensional things and attributes [40]. The primary function of graphical user interfaces is for users to have direct control over visual representations of items. This can be accomplished by using on-screen commands and interacting with menus referred to as ad hoc feedback, in which concurrently the user receives information through a unique display and projection of stated objects [41]. For less-trained employees, augmented reality delivers information and interactive instructions. They will be instructed on the processes using the AR assistance. It also makes training and education more participatory and gives immediate outcomes [33], [42]. The demand for custom-made solutions for human-robot collaboration is the most notable future visualization, and more user-friendly devices will be introduced for a better experience [43], [44].

6) SIMULATION

A system should be thoroughly tested before its implementation. Different forms of simulation, such as discrete events and 3D motion simulation, can enhance product or process planning in various situations [45]. Simulation finds applications in various areas, such as product development, testing, optimization, production process development, and the improvement of facilities. Weyer et al. [46] reported that simulation could assist production in the assembly line balancing. The simulation can help with machining scheduling that requires calculating robots' operating cycle times and allows for design and manufacturing competitiveness. From the standpoint of I4.0, simulation can be viewed as a supplementary tool for tracking the results of various parameter modifications [47]. In the same vein, simulation tools offer decision-making visualization capabilities, making them valuable in conjunction with other core technologies of I4.0 [48]. Simulation-based Computer-Aided Design (CAD) is crucial in ensuring a seamless operation of diverse and disparate CAD systems by modifying essential parameters to suit the operation requirements. Additionally, simulation can effectively reflect what-if scenarios and enhance process robustness [47], [49] to ensure actual operation works as planned.

7) ADDITIVE MANUFACTURING

Additive manufacturing is a collection of technologies to fulfil the requirements of I4.0 [50]. Due to its numerous advantages, additive manufacturing has become a current trend in manufacturing processes [51]. According to Haleem and Javaid [50], additive manufacturing is an important technology that has evolved into a critical product creation and innovation component. This revolutionary technology helps the industry to develop innovative products by addressing various challenges in the production system. Multiple manufacturing areas already use additive manufacturing [52], with the benefit of reducing products' time to market by creating a prototype without expensive equipment [53]. Designers are optimistic about implementing this initiative due to its greater freedom and flexibility.

Furthermore, additive manufacturing only deposits materials where they are needed. Thus, it reduces material waste [54]. According to Najmon et al. [55], quick prototyping, rapid tooling, and repair of materials such as metal, plastic, ceramic, and composite are the most common applications in the aerospace sector as they can construct freeform designs with complicated patterns, small production runs, and quick fabrication times, which makes it an ideal technology for manufacturers.

8) AUTONOMOUS ROBOTS

New challenges to make manufacturing processes more efficient and flexible have spawned a new industrial revolution, and autonomous robot navigation has become a crucial economic component [56]. Smart factories include distributed production lines that require internet-connected robots to carry things from one machine to another or for further processing [57]. Artificial intelligence (AI) tools collaborate to make smarter goods, equipment, and services. This is supported by autonomy, computing, communication, and control capacities. This adaptation entails cheaper manufacturing costs, shorter production periods, and shorter operating waiting times. Adaptive robots can also help design, produce, and assemble industrial systems [58]. An example of task allocation involves breaking down complex tasks into smaller sub-problems and utilizing a collection of modules to complete them. Integration of these modules at the end of each sub-task is necessary to achieve an optimal solution. One technology potentially enabling adaptive robotics is energetically autonomous, co-evolutionary robots. These robots incorporate scenario-based reasoning and operate based on a reaction-focused operating principle [36].

C. DRIVERS IN ADAPTING INDUSTRY 4.0

1) BUSINESS COMPETITIVENESS

Business competitiveness (BC) is achieved by improving corporate policies, mission, organizational structure, and target market [59]. As organizations strive to reap the benefits of advanced production strategies, adapting I4.0 will develop a capable company [60]. This has provided the organization with a good starting point for developing a strong position in the digital manufacturing industry. It also requires manufacturing companies to shift their company target and plan to invest in new technologies to remain relevant and competitive [59]. The strategic implementation of IoT enables companies to seize expanded market opportunities, thereby enhancing their competitiveness. This technology has undeniably played a significant role in improving the competitive position of companies by enabling strategic business expansion [61]. High-technology companies have the potential to enhance sustainable competitive advantage and foster skillful organizations [44], [62]. Hence, a review of previous literature reveals that business competitiveness is a driver for adapting I4.0.

H1: Business Competitiveness has a positive impact on the adaptation of Industry 4.0.

2) CUSTOMER SATISFACTION

The IoT-driven business model focuses on strengthening customer relationships, with the need to uphold respect for customers and vendors guided by the prevailing business culture [63]. The tendency of I4.0 is toward forming a communication network and channel for continuous data exchange. Such technology aims to have customer-oriented products and service adaptation. With this, the value for organizations and customers will increase [64], [65]. Manufacturers of hardware and machines can obtain data and information from the equipment. Once the data are collected and analyzed, the manufacturers and production can collaborate and align to produce better customer service [66]. Agile collaboration networks outline the horizontal integration trend that allows firms to focus on their core capabilities and this could be accomplished by providing personalized products in any market [67]. In the industrial internet, the customer's appraisal of the product is everything, based mostly on the customer experience, whether through product assessment or simply from the experience of using the product [68]. The objective is for the customer to acquire good value and a satisfying product while the manufacturer earns a good reputation [69]. Therefore, a literature review demonstrates that customer satisfaction (CS) is a driver for the adaptation of I4.0.

H2: Customer satisfaction has a positive impact on the adaptation of Industry 4.0.

3) FINANCIAL BENEFITS

Tang et al. [70] reported that I4.0 is driven by the financial benefits [71] gained with a proper adaptation of I4.0. It has proven to enhance value creation and grow sales volume. Technology tools, particularly AI, are essential in driving the emergence of new revolutionary business models that offer distinctive and up-to-date services. The optimal utilization of these advancements and technologies is essential to establish and maintain a sustainable business model [72], [73]. Previous research from Alkaraan et al. cite74 has defined that entire economies are positively improved with the adaptation of I4.0. According to Okunlaya et al. [75], smart service has opened the way for business growth as new technologies allow service delivery services to be digitized. Mourtzis et al. [76] and Petrillo et al. [77] agreed that adapting I4.0 enables customized products. This will impact cost reduction, determined by the energy resources, waste consumption, and highly efficient working conditions [78]. Based on the available literature, it becomes apparent that finance is one of the drivers for I4.0 adaptation.

H3: Financial Benefits have a positive impact on the adaptation of Industry 4.0.

4) OPERATIONAL IMPROVEMENT

I4.0 will enhance efficiency, improve utilization of time, increase flexibility, and improve quality [79], [80]. The operational improvement (OI) through intelligent systems will assist the employees in making qualified and valid decisions in a shorter period. Employees can monitor and control the production cycle by analysing technologically supported information and data [77], [81]. Müller et al. [82] and Enrique et al. [83] mentioned that with the adaptation of I4.0, the coordination of the material supply would be more efficient. In addition, introducing I4.0 through autonomous robots supports the employee in ergonomically critical situations. Specifically, non-ergonomic processes are likely to become automated to improve the safety status of manufacturing workers [77]. According to Jasiulewicz-Kaczmarek et al. [84], a smart factory will be equipped with ergonomic and safety concerns in production processes. Big data is one of the pillars of I4.0, targeted to agile decision-making and increase production efficiency and flexibility [6]. Autonomous robots and smart networks enable efficient production and precise work content. It will enhance the manufacturing process and improve precision and quality in operation [85]. Taking previous literature into account, it becomes evident that operational improvement (OI) is a driver towards the adaptation of I4.0.

H4: Operational Improvement has a positive impact on the adaptation of Industry 4.0.

D. RESEARCH FRAMEWORK

Based on the research problem, related theory, and literature review Figure 1 presents the framework used in this study.

III. METHODOLOGY

The researchers employed a quantitative research design to examine the relationship between the variables in achieving the research objective. This research aimed to test the conceptual model hypotheses in exploring the relationship between variables using a cross-sectional research design. The instrument used in this study is a survey questionnaire. Aligned with Structural Equation Modelling (SEM), the study results were analysed using Smart PLS software. SmartPLS was chosen because it can produce reasonable findings even with outliers, and when the data are not normally distributed [86]. In the development of the measurement tool, the instrument was designed to assess a particular content that was either adopted, adapted, or self-developed based on previous studies. Each measurement was addressed to assess an exact content that was referred from studies as mentioned in the literature review (see Appendix A and B).

The scales utilized in the instrument were ordinal, enabling individuals to express their level of agreement or disagreement with specific propositions. Different scales (a 6-point scale for drivers of I4.0 adaptation and a 7-point scale for adaptation of I4.0) were used to prevent a common method bias in the measurement scales [87]. Additionally, a pre-test of the developed measurement tool involved obtaining ratings from two academics and two industrial practitioners to assess the clarity and significance of the questionnaire. The respondents' feedback was carefully considered, leading to minor phrasing changes in the initial questionnaire.

The target population identifies the information that the researchers are looking for. The population is the group, using which the researcher wishes to generalize the study's findings, which comprises individuals with a certain trait. Consequently, the target population for this study consisted of CKD automotive manufacturing companies encompassing multiple CKD plants across two continents, Asia and South America. The unit of analysis proposed for this study was organization, and the element of the unit of analysis was the white collars, including middle management (Executive and Managers) and top management (Vice President, Chief Executive Officer, Chief Operation Officer, General Manager, and Senior Manager). These positions can reasonably be expected to possess specialized knowledge of I4.0 within the automotive operation. The population sample was selected using simple random sampling, a probability sampling technique where each instance has an equal chance of being included in the sample [88].

The sample size was determined using G-Power software analysis. In this study, the minimum sample size derived from G-power was 85. The sample size was calculated using G-Power with the following parameters: F-test, effect size $f^2 = 0.15$, alpha value=0.05, statistical power=0.80, and predictors=4. A survey was used for the tool implementation (Neuman, 2013), and it was conducted using Google Forms, which is suitable for reaching respondents across a wide geographic area where direct contact with the researcher is not feasible. This approach allows respondents to complete the questionnaire conveniently, resulting in a cost-effective data collection process. Another benefit of this strategy is that respondents can take their time filling out the questionnaire at their convenience at a cheap cost. A total of 150 surveys were completed and analysed, and no issues were encountered with respondents providing incomplete values, as they were required to complete all questions before proceeding.

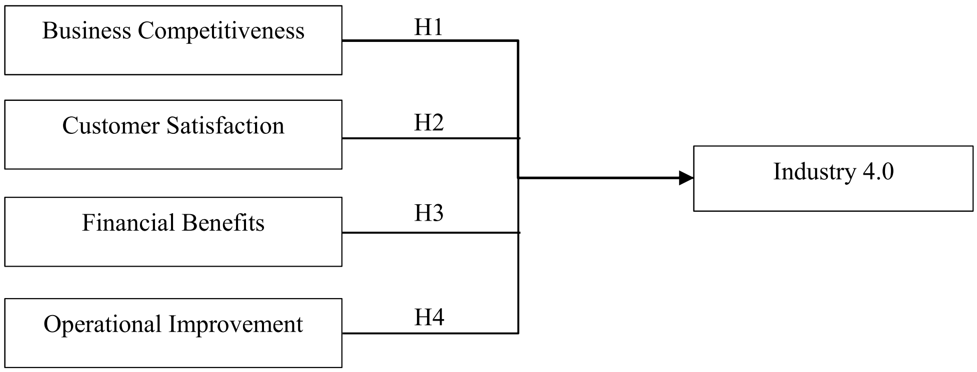

FIGURE 1. Research framework.

TABLE 1. Descriptive statistics of variables.

Construct	Min	Max	Mean
FB	2	6	4.64
OI	2	6	4.78
BC	3	6	5.67
CS	3	6	4.89
IND	2	7	5.97

IV. RESEARCH FINDINGS

The descriptive analysis provides information on the minimum value, maximum value, and the mean of the construct. The overall result of the descriptive statistic is shown in Table 1. PLS-SEM was used to analyse the measurement and structural models using the statistical software SmartPLS 4. This tool does not require a normality of data (Chin et al., 2003)., PLS-SEM was selected in this study for several reasons. Firstly, this is due to the exploratory nature of the research, which explores the drivers for I4.0 implementation. Second, the formative measurements in PLS do not require any further modifications [89]. A collinearity test was conducted to assess the presence of a common method bias since the data originated from a single source. The results indicate that the variance inflation factor (VIF) for all constructs (BC, CS, FB, and OI) ranged from 1.033 to 1.082. These findings confirm that common method bias did not pose a validity concern, as all VIF values were below the threshold of 3.3 [90].

The developed model was tested using a two-step approach [89]. First, the measurement model was examined to test the validity and reliability of the instrument. Then, the structural model was run to test the hypothesis developed. As the model consists of the reflective and formative parts, the reflective model was first assessed. Here, Cronbach's alpha (CA), average variance extracted (AVE), and composite reliability (CR) were assessed. In the first run of the PLS algorithm, the value of CA for CS was below the threshold value. Thus, the lowest loading, CS4 (0.485), was deleted. With the deletion of CS4, another cycle of the PLS algorithm shows the CA value for CS as 0.737, i.e. above the threshold value of 0.7. This indicates that the measurement model is valid and reliable [89]. Details of the convergent validity of the modified model are depicted in Table 2 and Figure 2.

This study follows the Heterotrait-Monotrait Ratio of Correlations (HTMT) procedure prescribed by Henseler et al. [91]. The HTMT value above 0.900 suggests a lack of discriminant validity [89]. Table 3 shows that the values for discriminant validity through the HTMT test were lower than 0.900. This proved that all construct questions were different and not interchangeable in their meaning. The highest value was 0.230, and the lowest value was 0.134. Therefore, it confirms the discriminant validity.

Next, to validate the formative construct, the redundancy analysis was used to determine whether the formatively measured construct is highly correlated with the reflective measurement of the same construct (Chin, 1998b). Using a global item, the beta value for I4.0 was 0.797, specifying that the formative indicators represent the construct adequately (Hair et al., 2017). The collinearity of the indicators and the significance of the indicators' weights are used to evaluate formative measures using a different set of metrics. These results are displayed in Table 4. The VIF for all formative indicators was below the critical value of 3.3 [90], which suggested that collinearity was not a serious issue. Next, the formative indicator's contribution to the formative construct score using the item weight significance was assessed. One indicator (IND5) was found not significant (0.078). However, according to Bollen (2011), removing causal indicators can be consequential as it determines the latent variable, and removing the causal indicators will change the nature of the variable.

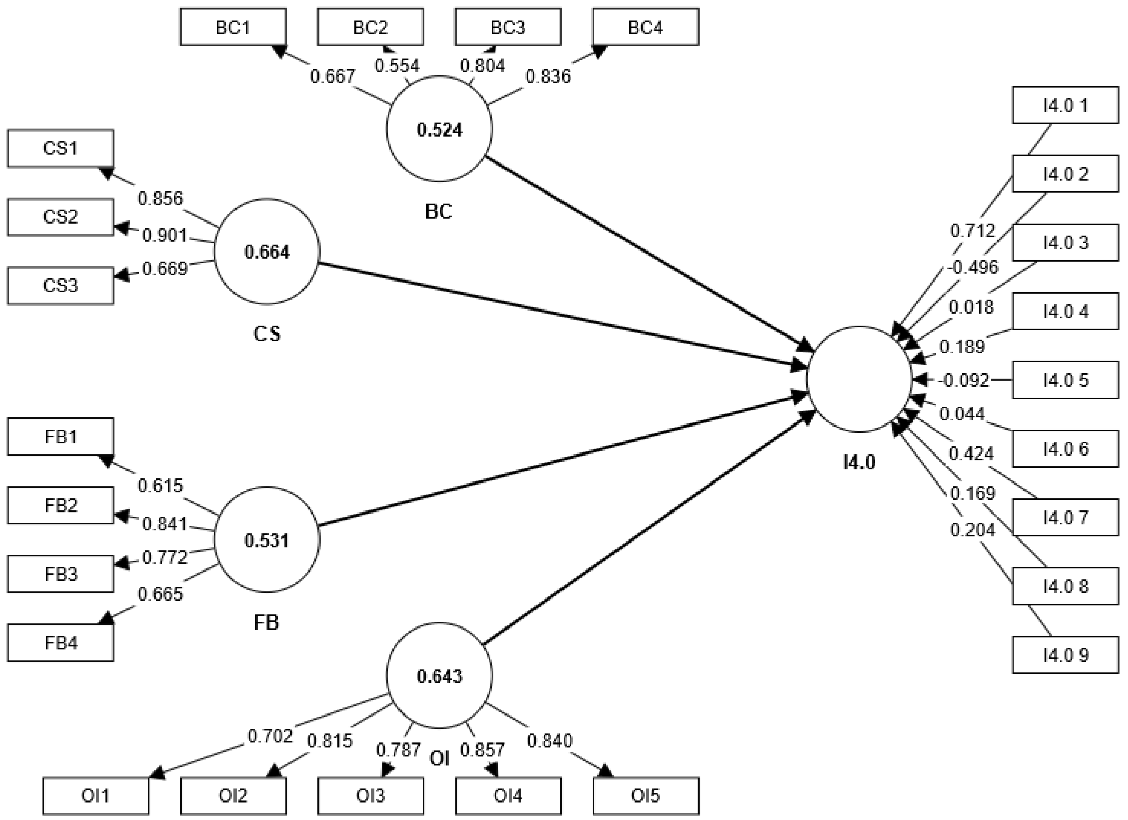

FIGURE 2. Modified PLS-path model.

TABLE 2. Convergent validity of reflective model.

Item Code	Measurement Items	Outer Loading	Cronbach's Alpha	CR	AVE
FB1	Provide business growth to increase profitability.	0.615	0.716	0.817	0.531
FB2	Give a positive impact on organizational economic growth.	0.841			
FB3	Reduce production costs.	0.772			
FB4	Improve the efficiency of the plant.	0.665			
OI1	Improve the decision-making speed.	0.702	0.865	0.900	0.643
OI2	Improve production system	0.815			
OI3	Increase flexibility.	0.787			
OI4	Increased transparency.	0.857			
OI5	Improve ergonomic.	0.840			
BC1	Skilled employees are created.	0.667	0.711	0.811	0.524
BC2	Capable organization developed.	0.554			
BC3	Shift in corporate planning.	0.804			
BC4	Change market opportunity.	0.836			
CS1	Gain a positive reputation.	0.856			
CS2	Increase consumer value.	0.901	0.737	0.854	0.664
CS3	Improve tailored capacity (flexibility allows customized products).	0.669			

After evaluating the measurement model, the significance of paths in the structural model by running the bootstrapping algorithm was assessed. When running the bootstrapping, Hair et al. [89] recommended that the minimum number of bootstrap samples should be at least as high as the number of valid observations in the original data set. According to [89], the 95% confidence level is used in most settings, implying that the p-value must be smaller than 0.05 to render the relationship under consideration as significant. A one-tailed test was used to determine the significance level, as the hypotheses generated in this study are the directional hypotheses [92]. Due to this justification, such predictions in directional

TABLE 3. Convergent validity of reflective model.

	BC	CS	FB	OI
BC				
CS	0.185			
FB	0.174	0.167		
OI	0.134	0.230	0.141	

TABLE 4. Convergent validity of formative model.

Item Code	Measurement Items	VIF	p-value	p-value
IND1	IoT: Most of the devices in our company are interconnected via the internet to allow them to connect, interact, and exchange data.	2.045	10.412	0.000
IND2	Cybersecurity: Our company protects the privacy, confidentiality, and integrity of its digital information through the implementation of a cybersecurity system.	3.283	5.931	0.000
IND3	Cloud Computing: Our company uses a network of remote servers hosted on the internet to store, manage, and process data, rather than a local server or a personal computer.	1.672	6.340	0.000
IND4	Additive Manufacturing: Our company utilizes the additive manufacturing technology (e.g., 3D printing) to guarantee the products are unique with low production cost.	2.486	8.249	0.000
IND5	Augmented Reality: Our company has applied the augmented reality technology to integrate virtual images with real-world objects.	1.624	1.418	0.078
IND6	Big Data: Our company manages and analyses huge of data and information to support its decisions in achieving its objectives effectively.	2.173	7.287	0.000
IND7	Autonomous Robot: Our company uses autonomous robots to improve the efficiency of production lines and optimize the system.	2.732	7.828	0.000
IND8	Horizontal and Vertical Integration: All sub-systems in the company into one system to enable the system to deliver overreaching functionality.	1.671	4.412	0.000
IND9	Simulation: Our company evaluate the effectiveness of the changes in machine configuration, process flow and plant design by using simulation.	2.262	6.645	0.000

hypotheses were tested with a one-tailed test with critical values of 2.33 (significance level = 1%), 1.645 (significance level = 5%), and 1.28 (significance level = 10%). Figure 3 and Table 5 exhibit the results of the hypothesis testing from the bootstrapping analysis.

Resulting of the bootstrapping processes, p-values, t-values and path coefficients were used to test the statistical significance of the paths. As shown in Table 5, H1 presents a relationship of BC on I4.0 adaptation at a 5% significant level with the outcome of the path coefficient=0.294, t-value=3.698, and p-value=0.000. According to Hair et al. [89], the p-value smaller than 0.05 renders a significant relationship, showing that the hypothesis of BC on I4.0 is supported. H2 shows a path coefficient of 0.593, a t-value of 8.410, and a p-value of 0.000. The p-value of 0.000, shows that the hypothesis of CS positively affects the adaptation of I4.0.

H3 predicts the relationship between FB and the adaptation of I4.0. Based on bootstrapping analysis, the result shows that path coefficient=0.193, t-value=1.550, p-value=0.061.

Thus, H3 is not supported as the p-value is higher than 0.05. Finally, the last hypothesis, H4, predicts the relationship between OI and adaptation of I4.0. The finding showed that H4 is supported at a 5% significance level (path coefficient=0.125, t-value=1.777, p-value=0.038).

The R^2 determines how much of the variance in endogenous constructions can be explained by external constructs. It represents in-sample predictive power [89]. R^2 values of 0.26, 0.13, and 0.02 are considered substantial, moderate, or weak, respectively [93]. The value of R^2 for I4.0 is 0.583 considering the variables have substantial determination.

The evaluation of f^2 indicates how greatly the contribution of an exogenous variable to an endogenous variable is [93]. Hair et al. [89] reported that the f^2 with values of 0.02, 0.15, and 0.35 indicates small, medium, and large effects. The f^2 of BC and CS are 0.295 and 0.668, respectively, which indicates a large effect. Meanwhile, FB and OI had a small effect size with an effect size of 0.029 and 0.063, respectively.

TABLE 5. **Bootstrapping analysis.**

Path	Path Coefficient	Std. Error	t-value	p-value	Decision
H1: BC→I4.0	0.294	0.079	3.698	0.000	Supported
H2: CS→ I4.0	0.593	0.070	8.410	0.000	Supported
H3: FB→ I4.0	0.193	0.125	1.550	0.061	Not Supported
H4: OI→ I4.0	0.125	0.070	1.777	0.038	Supported

TABLE 6. **Derived from literature indicators for Industry 4.0.**

Industry 4.0	Literature
Augmented Reality: Applied augmented reality technology to integrate virtual images with real-world objects.	Buttner et al. (2017); Syberfeldt et al. (2016); Salkin et al. (2018); Segovia et al. (2015)
Big Data Analysis: Manages and analysis huge amount of data and information to support its decisions in achieving its objectives effectively.	Ministry of International Trade and Industry (2018): Zhou et al. (2015); Bahrin et al. (2016); Obitko and Jirkovsky (2015); Zhang et al. (2017)
Simulation: Evaluate the effectiveness of the changes of machines configuration, process flow and plant designs by using simulation	Mourtzis et al. (2015); Weyer et al. (2016); Gavish et al. (2015)
Cloud Computing: Uses a network of remote servers hosted on the Internet to store, manage, and process data, rather than a local server or a personal computer,	Leitão et al. (2016); Rußmann et al (2015); Wu et al. (2015)
Internet of things (loT): Interconnection via internet to allow them to connect, interacts, and exchange data.	Cao et al. (2009); Chow et al. (2006);Tu et al. (2017); Fasth (2005)
Cybersecurity: Protects for its privacy, confidentiality, and integrity of its digital information through the implementation of cybersecurity system	Gaub (2016); Salkin et al. (2018)
Horizontal and vertical integration: Integrate all sub-system in the company into one system to enable the system to deliver overreaching functionality	Salkin et al. (2018); Wang et al. (2016)
Additive manufacturing: Utilized the additive manufacturing technology to guarantee the products are unique with low production cost.	Gaub (2016); Gress and Kalafsky (2015)
Autonomous robot: Uses autonomous robots to improve efficiency	Wittenberg (2016); Michalos et al.(2010); Kochan (2005); Wang et al. (2016)

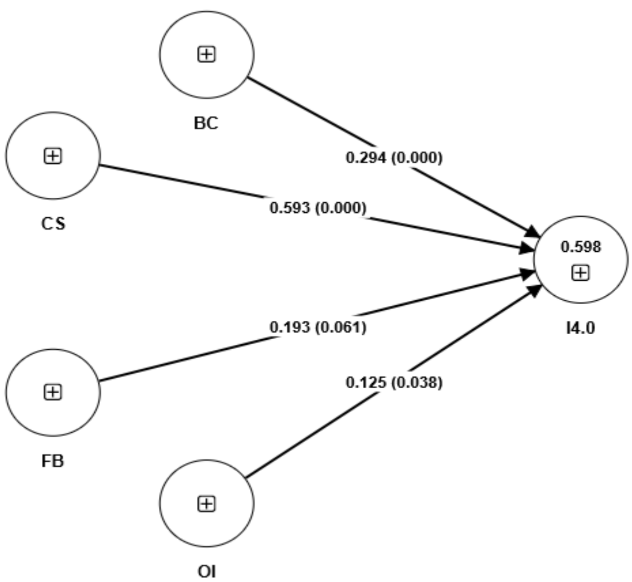

FIGURE 3. **Bootstrapping graphical output of path coefficients and P-values.**

The predictive relevance value, also known as the Q^2, examines whether the data points of indicators in the reflective measurement model's endogenous variable can be accurately predicted (Wong, 2013). According to Hair et al. [89], the relative measurements for the Q^2 are 0.02, 0.15, and 0.35, respectively, denoting constructs with small, medium, and large predictive values. Predictive relevance values less than 0.02 should be ignored since they are insufficiently predictive. Q^2 for I4.0 has a rating of 0.246, indicating medium predictive relevance.

V. DISCUSSION

To identify the drivers of I4.0 adaptation, the researchers combined the measurements from several previous studies into a collection of common variables (FB, OI, BC, and CS). Thus, the current study developed four direct hypotheses to empirically test a framework encompassing the drivers of I4.0 adaptation. Based on the findings, it was determined that three drivers (H1, H2, and H4) positively affect I4.0 adaptations, while H3 has no significant effect. The positive impact of the three drivers, OI, BC, and CS, on the adaptation of I4.0 is evident. Based on these findings, CKD automotive manufacturers could prioritize these three factors as key drivers for successful I4.0 adaptation.

The positive relationship between BC on I4.0 is consistent with the previous research from Mithas et al. [60], Korcsmáros and Csinger [61] and Mohamed and Eltohamy [59]. According to Mithas et al. [60], the adaption of IoT will enhance competitiveness by increasing market opportunities due to strategic business. The company adapting

TABLE 7. Derived from literature indicators for drivers of Industry 4.0.

Drivers of Industry 4.0		Literatures
Financial Benefit	1. It has opened the path for the business growth as the new technologies enables the digitalization and resulted to increase profitability.	Stock and Seliger (2016)
	2. It gives a positive impact in the financial and has proven to enhance the value creation and support economic growth.	Petrillo et al (2018), Santos et al (2017)
	3. Process transparency indirectly production cost can be significantly reduced	Balasingham (2016), Petrillo et al (2018)
	4. Industry 4.0 will support to provide higher efficiency to the complete process	Petrillo et al (2018)
Operational Improvement	1. The intelligent system will assist worker to make qualified and valid decision in a shorter period.	Petrillo et al (2018)
	2. Better process control will be obtained with the adaptation of Industry 4.0 approach	Balasingham (2016), Ministry of Intenational Trade and Industry (2018)
	3. Internet of Things technologies, cloud-based control, and autonomous machines contributed as a major improvement that resulted to the increase of flexibility to the operation.	Petrillo et al (2018), Santos et al (2017)
	4. Usage of RFID will improve the transparency of the product in the production	Gilchrist (2016), Petrillo et al (2018), Santos et al (2017)
	5. The aims of Industry 4.0 is to create the smart factory with the features of ergonomic and safety concern	Petrillo et al (2018)
Strategic Change	1. Created skilled employee with considerable expertise in embedded systems and automation engineering, providing with a good starting point.	Kagermann (2015), Ministry of Intenational Trade and Industry (2018)
	2. Capable organization were developed as companies are constantly trying to exploit the benefits of sophisticated production strategy.	Ministry of Intenational Trade and Industry (2018)
	3. This competitiveness hinges on the ability to transform by responding to market shifts and technological trends.	Ministry of International Trade and Industry (2018)
	4. Increasing of market opportunities due to strategic business areas is major focus in the context of the loT, and it is undoubtedly enhanced the company competitiveness.	Balasingham (2016), Kiel at al (2017)
Customer orientation	1. Goal is for the customer to gain value and a satisfying product and for the producer to gain a good reputation.	Gilchrist (2016)
	2. The target of such automation is to have individual customer-oriented adaptation of products and services that will increase value for organizations and consumers.	Kiel at al (2017)
	3. Agile Collaboration Networks allowing manufacturers to focus on their competencies by offering tailored capacity in any market.	Balasingah (2016), Santos et. al. (2017)
	4. Manufacturers and production can collaborate and align to produce better services to the customers.	A. Khan and Turowski (2016)

to I4.0 strives for competitive advantages and long-term victory (Korcsmáros and Csinger [61]). An organization's competitiveness is measured by its capacity to adapt and transform in response to market shifts and technological trends. This is achieved through implementing I4.0 in manufacturing processes [59]. Hence, it is proven that BC will support the I4.0 adaptation in the CKD automotive context. CKD manufacturers seek efficiency, quality, innovation, and data-driven decision-making to compete in a challenging business.

Additionally, findings also endorse the results from Klos et al. [63], Javaid et al. [69], and Santos et al. [67] that CS has a positive relationship with I4.0. The tendency of I4.0 is toward forming a communication network and a channel for continuous data exchange. Such technology aims to have customer-oriented products and service adaptation. With the appropriate technology function, the value for organizations and customers will also increase [63]. The customer's product evaluation is everything in the industrial internet, especially when it is related to customer experience. This can be achieved through product assessment or simply from the experience of using the product. The goal is for the customer to gain value and receive a satisfactory outcome for the producer to establish a good reputation [68], [69]. In summary, CS is a driver for CKD manufacturers to adapt to I4.0, enabling them to produce quality products, increase responsiveness, and drive innovation, ultimately leading to higher customer satisfaction.

Additionally, the positive relationship between OI in I4.0 is consistent with research from Enrique et al. [83], Javaid et al. [85], and Müller et al. [82]. I4.0 will enhance efficiency, improve utilization time, increase flexibility, and improve quality. According to Müller et al. [82]. I4.0 allows efficient coordination of the material supply. Additionally, it will enhance the quality of the product and operational process throughout the product life cycles and between various locations. The findings from Javaid et al. [85] seem consistent with other research, which found Internet of Things, cloud-based control, and autonomous machines contributed to a significant improvement, which resulted in the increase in productivity to the operation. In a nutshell, OI becomes a driver for I4.0 by utilizing advanced technologies and data-driven decision-making to enhance efficiency, productivity, quality, and innovation, leading to improved operational performance and competitiveness.

Contrarily, the findings of this study suggest that FB does not play a significant role in driving the adaptation of I4.0. This perspective aligns with the viewpoint presented by Luthra et al. [94], who argue that FB may not be the primary driver behind the adaption of I4.0, due to the substantial initial financial investment required. However, it underscores the importance of long-term planning in effectively addressing this concern, particularly considering the uncertainties associated with the successful implementation of I4.0 [95]. Furthermore, in the context of CKD automotive manufacturing, the emphasis leans towards cost reduction strategies compared to large-scale automotive manufacturing, as the primary purpose of CKD plants is to achieve cost efficiencies [96].

VI. CONCLUSION, LIMITATIONS AND RECOMMENDATIONS FOR FUTURE STUDY

The study has contributed to the existing knowledge in understanding the drivers for I4.0 adaptation among the CKD automotive industry in multiple countries. Four drivers (BC, CS, FB, and OI) were developed based on the conceptual framework. A cross-sectional quantitative analysis was used to examine the four hypotheses. The study used the PLS-SEM approach for data analysis with the application of the Smart-PLS tool. The questionnaire was distributed using Google Forms, and 150 responses were collected to analyze the data. The result indicated that three hypotheses were supported, and one hypothesis was not. According to the findings, three drivers, BC, CS, and OI, positively affect I4.0 adaptation.

It is necessary to explain the limitations and prospects of the study. Further study will extend the current one using a mixed-method approach. Applying both methods will contribute significantly to provide a holistic view of the I4.0 adaptations in the CKD automotive manufacturing industry. It will provide a breadth and depth to understand the phenomena that neither qualitative nor quantitative approaches alone could support in answering the research questions. The qualitative phase is able to explain further, validate, and triangulate the quantitative study results [97], [98]. In addition, through R^2 analysis, only 58.1% of the drivers for I4.0 adaptation were explained by the shared effects of BC, CS, and OI. Hence, future research will investigate other factors, such as supportive government policies proposed by Krishnan et al. [99] and Luthra et al. [94].

APPENDIX A

See Table 6.

APPENDIX B

See Table 7.

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