Practising circular economy performance in Malaysia: Managing supply chain disruption and technological innovation capability under Industry 4.0

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Abstract
In response to environmental awareness and financial return, manufacturing firms are increasingly concerned about practicing circular economy performance (CEP). The lack of comprehensive evidence on the integrated technology capability in IR4.0 driven based supply chain management literature has motivated this study to investigate how the company manages the disruption of Industry 4.0 technology and its impact on CEP. Data were obtained from 130 Malaysian manufacturing companies. Data were analyzed using structural equation modelling using PLS-SEM. The results showed CEP's positive and significant effect on managing supply chain disruption and technological innovation capability (TIC). Positive relationships prove that CEP has a considerable influence on the manufacturing industry. The mediating results found that the TIC has played a complimentary mediation effect to support the nexus of managing supply chain disruption, supply chain disruption recovery and CEP. Supply chain managers are encouraged to control interference problems and improve effective communication and teamwork.

Keywords: *Circular economy performance; Supply chain disruption orientation; Supply chain disruption discovery; Technological innovation capability; Industry 4.0*

Practising circular economy performance from managing supply chain disruption and technological innovation capability under Industry 4.0

1. Introduction

In developing countries, the manufacturing industry has contributed to the country's economic growth and prosperous society. However, rapid industrialisation has increased resource depletion, environmental pollution and acid waste (Bui et al., 2021; Chien et al., 2021; Wang & Feng, 2019). To avoid the negative impact on the environment, firms have shown interest to practice a circular economy (CE). CE is a concept introduced by the European Union to replace the linear economy for sustainability. The concept focuses on promoting and providing human access to environmentally friendly practices and a responsible society (Moraga et al., 2019; Tseng et al., 2021). Fernando et al. (2021) postulated that firms need to practice circular economy-based eco-innovations to remain relevant in the market.

Malaysia has two scenarios to practice the CE with support of the Industry 4.0 (IR4.0) technology. First, the government has implemented strict standard operating procedures to curb the spread of Coronavirus Disease 2019 (COVID-19). As a result, the manufacturing firms have experienced major disruption as fewer workers are allowed to work in the manufacturing plants. As a result, firms have had to lay off workers to reduce company costs. In the first 14 days of the movement control order policy, Malaysian manufacturing companies suffered heavy losses when production and export products ceased. Major supply chain disruption is when some manufacturing firms rely on imported raw materials from China. The border also has been closed, resulting in a reduced supply of migrant workers in the manufacturing sector. The local manufacturing firms have to find a way to use existing raw materials and recover the scrap. Sensor, digitalisation and automation have to be deployed to monitor production during the movement control order. Second, the recent government initiative to promote digitalisation in the supply chain has attracted the industry to deploy the IR4.0 technology. Nowadays, the digitalisation of technology has changed business operations, from dependency on the low skills workers to high skills workers while improving productivity and business efficiency. The deployment of IR4.0 has critical to support circular economy operations, especially to repair, refurbish and recycle hazardous chemicals, waste and other physical hazards.

The same situation of COVID-19 has happened globally. For example, Orlando et al. (2022) argued that the COVID-19 outbreak has disrupted the European Union and found that firm's innovation has impacted the most resilient supply chain. Hohenstein (2022) confirmed that the COVID-19 pandemic had caused long-term disruption in firm operations and globally dispersed supply chain networks based on the German country setting. Spieske and Birkel (2021) postulated that IR4.0 could mitigate supply chain risks during COVID-19 outbreaks. From Australia, Hopkins (2021) argued the COVID-19 outbreak has disrupted the supply chain and increased risk. The firms need to digitalise and automate the supply chain operation with innovation to overcome this. Based on the previous literature, we argue that the firms need to practice the circular economy to anticipate the resource supply disruption and utilise the IR4.0 technology to be resilient among competitors. It is critical to examine the supply chain digital disruption of IR4.0 technology and its impact on circular economy outcomes. The results can be useful to benchmark and manage the supply chain disruption to other countries.

The digitalisation of supply chain management can improve productivity and resource efficiency by utilising smart digital technology to manage the upstream and downstream ecosystems in the supply chains (Tseng et al., 2021; Yong et al., 2019). For instance, Awan et al. (2021) argued that managing CE requires digital enable technology to uncover relationships from information and data for useful data-driven decision-making. However, there is less comprehensive research on managing supply chain disruption while manufacturing relies on digital technology. Recent disruption due to the COVID-19 has impacted the supply chain flow especially when the country depends on imported products and materials for production (Koirala & Acharya, 2020). Due to limited material resources and delayed delivery due to the COVID-19 pandemic, the manufacturing firms began reducing production. Physical activities need to be reduced and replaced by automation and online meetings for communication purposes. Since then, the CE that supports IR4.0 technology has played a vital role in the manufacturing sector. The manufacturing firms must design the mitigation strategy to overcome the supply chain disruption, especially at the upstream level.

This has led to the manufacturing-focused countries facing supply chain disruption issues due to COVID-19. It has boosted the adoption of digital and intelligent technology. An IT-driven digital transformation that enhances machine-human correlation to improve productivity and reduce cost have been adopted for business competitiveness. According to Moosavi et al. (2021), the advanced digitalisation paradigm allows manufacturing firms to improve flexibility and performance. As the manufacturing firms in the developing countries focused on low cost, productivity, and operational flexibility, the adoption of IR4.0 impacts the manufacturing performance (Luthra & Kumar, 2018). The adoption of IR4.0 is not only driven by the manufacturing firms that tend to improve business performance but also depends on government support and policy. However, further debate on how the industry policy can assist the success of the manufacturing industry and national competitiveness is required (Dalenogare et al., 2018).

In addition, inflation and currency exchange has created uncertainty regarding imported raw materials and caused an increase in total production costs. The manufacturing companies need to figure out how to utilise the end-life-products and leftover materials for remanufacturing. The manufacturing firms need to design a production ecosystem that ensures no waste and improves the economic values added in the supply chains. Despite the advanced development of the IR4.0 in supply chain management to handle environmental degradation and resource scarcity, little is known about how manufacturing firms can handle the supply chain disruption using IR4.0 technology to support the business operations. It is equally critical to examine how the manufacturing firms can manage the IR4.0 technological disruption to improve the CEP. The previous scholars have been discussed the interconnection between the circular economy performance and IR4.0. For example, Nascimento et al. (2019) argued that IR4.0 technology could optimise circular economy operations. Di Maria et al. (2022) concurred that IR4.0 technology incorporated in smart manufacturing has significantly improved circular economy outcomes. Yet, it is challenging to predict how the IR4.0 technology supports sustainable CEP in the long term. Although CE and IR4.0 have been discussed in the literature, Rajput and Singh (2019) argued that integrated IR4.0 in the supply chain is hard to achieve when the circular economy has not been placed as the enabler. Belhadi et al. (2022) suggest that future study needs to capture the improvement of sustainable assessment indicators for a well-integrated circular economy and IR4.0.

There are issues related to the lack of infrastructure and internet-based networks to support the IR4.0 driven supply chain in managing CE practices. To effectively implement IR4.0 concepts, sufficient infrastructure, information technology-based facilities, and technological innovation capabilities (TIC) are required (Bag et al., 2021; Bui et al., 2021; Chien et al., 2021). A lack of internet access hampers Industry 4.0 initiatives. Furthermore, internet-based technology is not equally accessible in urban and rural areas in some developing countries, which stymies long-term business growth (Alnajem et al., 2021; Chien et al., 2021; Bedekar, 2017). For instance, Pourmehdi et al. (2021) argued that little research shows how the manufacturing industry in developing countries can overcome the challenge to integrate the IR4.0 technology and sustainability in the supply chains. Although most of the production is focused on developing countries, technology, infrastructure, and technical knowledge are still insufficient to support CE based IR4.0 implementation. The government has just set up the guideline of IR4.0 and policy. This study argues a lack of research findings because the IR4.0 and CE movement in developing countries is still in the early stages. The firms have uncertainty about adopting IR4.0 because of disruption issues and are not ready with technology know-how. There are two research questions:

- Do the Industry 4.0-driven manufacturing firms have a proper mitigation strategy to avoid the technological disruption in adopting the circular economy practices?
- To what extent can the TIC mitigate the Industry 4.0 disruption to manufacturing firms in developing countries?

The contributions in this study are as follows. (1) A limited study uses ecological modernisation theory to describe the complexity of managing digital disruption in the supply chain and integrate it into the circular economy initiative; (2) Little is known about how the mitigation strategy on the IR4.0 driven manufacturing firms can overcome supply chain disruption, recovery issues, and CEP. As a low-cost oriented manufacturing strategy and enhanced business competitiveness, manufacturing firms that do not have a strategic plan on IR4.0 adoption will struggle in the infancy stage. Our study has provided evidence of the mediating effect of TIC to enhance the firm's supply chain mitigation strategy and circular economy performance; (3) To the best of our knowledge, there is no study to examine the complimentary mediation effect to support the nexus of managing supply chain disruption, supply chain disruption recovery and circular economy performance; and (4) The research model can serve as a handy counter for practitioners on how to mitigate the disruption risk and remove the circular economy barriers using IR4.0 technology.

To fill the research gap, this study has focused on IR4.0 disruption that challenges the early adopters and examines the circular economy performance from the micro perspective using a manufacturing firm as a unit of analysis. In a developing country like Malaysia, integrating CE and IR4.0 is a relatively new concept. It requires precise guidelines and best practices to be correctly understood and used in business. This study has been divided into six sections. The first section briefly describes the motivation of the study. Section 2 discussed the relevant literature review that establishes the research model and outlines the hypotheses of this research. The methods used and the analysis results in this study are presented in sections 3 and 4. Section 5 shows the discussion. Finally, the limitation and conclusions are presented in section 6.

2. Literature Review

Sustainable manufacturing is a concept that brings about a safer environment through efficiency in using existing energy and water resources and helping the company reduce the cost of raw materials by recycling the waste. IR4.0 has emerged as a digital transformation and improved manufacturing performance in the modern era. This study has utilised the ecological modernisation theory (EMT) to explain the variables in the research framework.

The theory is defined as an innovation to the systematic eco in modern times. Ecological modernisation aims to link advanced modernisation and planning systems through advanced innovation and technology (Chien et al., 2021; Jänicke, 2008). One of this theory's advantages is that it enhances communication efficiency between the two parties and diversifies the industry (Christoff, 1996). Sehnem et al. (2021) argued that EMT has contributed to the advancement of circular economy practices that assist in understanding effective circular and sustainable operations. Fernando et al. (2022a) suggest that citizens need to be aware of the benefit of a circular economy and its impact on well-being. Social well-being has been conceptualised in the EMT. The relationship of supply chain disruption, technical innovation and ecological impact on the circular economy performance has been explained using EMT. The literature review section has been built based on the topic's relevance to the previous studies. We also consider the literature patterns by developing a theoretical framework. The discussion of the subtopic is as follows:

2.1. Circular Economy Performance

The CEP aims to manage the environmental issue by focusing on waste treatment and eliminating waste after use (Alnajem et al., 2021; Saavedra, 2018). The CEP has indicated how the firms can remanufacture disposal materials and waste using sustainable resources and practices. According to Saidani et al. (2019), the CE is part of the economic systems that reduce, recycle, and recover materials in three stages of the supply chain process: production, distribution, and consumption. According to INC (2017), there are four benefits of CEP specifically to the industry: (1) reduces environmental damage, (2) reduces dependence on imported materials, (3) avoids damaging the environment from excessive consumption of natural resources, and (4) reduce air pollution. In addition, the firm's CEP implementation will be more competitive by reducing energy consumption and cost savings and controlling waste. Therefore, we define the CEP as the outcome of a sustainable production and consumption process.

2.2. Managing supply chain disruptions

Supply chain disruption has become an obstacle for manufacturing companies that aim to compete globally. Supply chain disruptions are a combination of unforeseen triggering events. If the firms are unable to manage it, it has consequences that will jeopardise the flow of materials and business operations (Bui et al., 2021; Bode & Wagner, 2015; Tseng et al., 2021). The supply chain disruption will impact the total supply chain cost and economic performance. According to Hendricks and Singhal (2005), firms that experience supply chain disruption will experience sales, stock return, and profitability loss. To handle the supply chain disruption and data-driven decision making, Kinsey (2016) suggested that firms replace traditional supply chain management with IR4.0 technologies such as the Internet of things (IoT) and Artificial intelligence. This study conceptualises supply chain disruption into three domains: (1) Managing Supply Chain Disruptions (MSCD), defined as a combination of ideas from all management staff to plan ways to reduce disruption issues and prevent material flows and business activities from being significantly abnormal (Bode & Wagner, 2015); (2) Supply Chain Disruption Orientation (SCDO), defined as general awareness and responsiveness of an organisation, responsibility, earnestness to and acceptance of the opportunities from learning the supply chain disruptions (Bode et al., 2011); (3) Supply Chain Disruption Discovery (SCDD), defined as the function of controlling disruptions and formulating problem-solving plans (Bode & Macdonald, 2017; Macdonald & Corsi, 2013).

2.3. Technological Innovation Capability

TIC is an essential factor in competing between firms in the manufacturing industry, especially at the global level (Guan & Ma, 2003; Yong et al., 2019). According to Wang et al. (2008), TIC is a complex and uncertain concept that is hard to determine. It is typically measured using quantitative and qualitative criteria. There are seven dimensions of TIC: (1) manufacturing capability, (2) resource exploiting capability, (3) learning capability, (4) strategic capability, (5) organisation capability, (6) R&D capability and (7) marketing capability (Guan et al., 2006). This study defines the TIC as the firms' ability to be innovative using the IR4.0 technology to improve the CEP. Therefore, the firms need to explore the uniqueness and be innovative using technological capability. TIC is a comprehensive set of company features that will support and improve business strategy through technological innovations (Guan & Ma, 2003).

2.4. Hypotheses Development

A hypothesis development explains the relationship among variables and requires support from the literature on the subject. The proposed hypothesis with the statistical test is expected to extend the current literature on the nexus of supply chain disruption, TIC and CEP.

SCDO is defined as the firm's awareness, concerns, and determination in providing opportunities and solutions to disruptive problems. According to Bode et al. (2011), firms oriented to supply chain disruptions can evolve through learning from past experiences. These disruptions will occur in every firm. Therefore, rapid response is required from top management. Structuring and updating infrastructure can reduce threats and disruption issues (Ambulkar et al., 2015). Yu et al. (2019) argued that SCDO includes alertness activities that benefit companies to increase response to SC interference through early warning notifications. Kwak et al. (2018) postulated that supply chain innovation could improve performance and enhance risk management capabilities. This study argues that firms that deployed supply chain disruption orientation could mitigate the risk through the ability to handle technological innovation.

H1a: There is a positive and significant relationship between SCDO and TIC.

Managing SC is closely associated with TIC in the manufacturing industry. SC disruption will hurt the manufacturing performance. The problem is an increase in anomalies when orders are in transit for delivery to other departments. The consequence is that the company suffered losses, and the product is lost during the transit process, and the supplier must bear and compensate for each lost item. Thus, implementing TIC in managing SC can minimise uncertainty problems and maximise profit. For example, the TIC introduced is Radio Frequency Identification (RFID) to monitor each product's movement from factory to consumer (Hill et al., 2016). RFID chips placed on all products help the company detect any anomalies that may exist quickly.

H1b: There is a positive and significant relationship between MSCD in IR4.0 and TIC.

The previous studies have examined the relationship between SCDD and TIC in the manufacturing industry. Interruptions in the supply chain are often viewed as a significant issue in the manufacturing industry. According to Blackhurst et al. (2011), each firm can deal with supply chain issues through a redesigned system. In phases, the redesigned system in the supply chain can solve interference problems such as interruption on raw materials and intermediate goods. In today's advanced technology industry, system technologies such as big data, AI, and IoT are very useful in the manufacturing industry and function in detecting interference problems in the supply chain (Bui et al., 2021; Dubey et al., 2019). Blackhurst et al. (2011) support the application of TIC systems in solving SC interference, such as through the construction of monitoring systems the use of Blockchain and FRID that enhances information access in firms. It can directly identify the problem and the solution quickly. According to Yong et al. (2019), using a functional TIC monitoring and analysis system provides an early warning to the firm to be prepared for interference in the SC. Seo et al. (2014) argued that technology drives innovation capability and knowledge expansion in the supply chain. Therefore, the firm capability to handle IR.40 innovation in the supply chain will impact the sustainable competitive advantage.

H1c: There is a positive and significant relationship between SCDD and TIC.

This hypothesis explains the relationship between SCDO and CEP through support from previous literature. This study involving SCDO shows how disruption occurred in the past in providing a flatform solution through CEP combination. According to Rahman (2020), this literature is discussed because CEP has a limited scale for interference problems in the supply chain. Although the relationship between SCDO and CEP is different, CEP helps the firm a little with infrequent disturbances (Rahman, 2020). For example, through the CEP system, the firm can recycle pre-consumer and post-consumer products that can source 24% of supply during a disruption (Gaustad, 2018). Next, CEP's combination shows CEP's ability to increase resilience and reduce dependence on SC. After that, other firms' knowledge and experience can also be applied as additional knowledge to all firms.

H2a: There is a positive and significant relationship between SCDO and CEP.

MSCD in IR4.0 and CEP is a good combination of positively impacting the manufacturing industry. Managing supply chains prevents production and product delivery (Mativenga, 2017). These issues include the machine breakdown of the production line and the delay in product delivery due to technical problems. The advanced technology of IR4.0 in the manufacturing industry also provides smooth manufacturing processes. Through this technology and IR4.0 support, firms can get faster information and more accurately (Manavalan & Jayakrishna, 2019; Tseng et al., 2021). Furthermore, IR4.0 contributes to CEP's sustainability and efficiency using the IoT to collect community waste data. Recycling resources can minimise waste of resources, and implementing IR4.0 in CEP has positive effects (Angioletti, 2017), such as producing quality and innovative products. The effective synergy between IR4.0 and circular economy has improved the sustainability of logistics (Bag et al., 2022). The CEP can stimulate SC's growth and management within the company through energy recovery and environmental awareness. Thus, the positive effects of combining these two concepts in manufacturing make the process more orderly through the introduction of Corporate Social Responsibility (CSR) within the company on the importance of environmental protection during production (Manavalan & Jayakrishna, 2019).

H2b: There is a positive and significant relationship between MSCD in IR4.0 and CEP.

Fernando et al. (2022b) suggest that the firms need to incorporate the strategic circular business models using Industry 4.0 technology. The SCDD is closely associated with CEP in the manufacturing industry. The CEP reduces the cost of resource use in inventory through re-use and recycling methods in the list (Alnajem et al., 2021; Paul, 2014). Simultaneously, ideal plans are developed and mitigation forecast to control interference problems during production and demand processes. Paul (2014) argued that the combination of SCDD and CEP in the industry had opened many solutions to interference. CEP's concept can solve this problem through CEP's idea to attract manufacturing firms to reduce unnecessary processes, recycle, and remanufacture by obtaining stock to avoid running out of supply resources.

H2c: There is a positive and significant relationship between SCDD and CEP.

The manufacturing industry's development is now facing the constraints of material resources due to the increasing growth of firms and the pollution disruption. It is argued that the supply of materials is unbalanced with the production patterns. For example, to curb corruption and increase the economy's purchasing power, China has begun to take steps in the economic transformation to stay developed and in line with environmental sustainability (Chien et al., 2021; Tseng et al., 2018; Tseng et al., 2021) through CEP TIC's practice in its country. CEPs and TICs function to balance economic growth and protect the environment. These technological developments include the use of IR4.0 in the company's operations. Therefore, it can achieve sustainability by integrating CEP and TIC, such as IR4.0, at a better level (Rajput and Singh, 2019). The correlation between TIC through IR4.0 and CEP has many positive effects on environmental sustainability and improves the company's living standards and economy (Ghobakhloo, 2020). Yadav et al. (2020) argued that sustainable production could produce better products by integrating IR4.0 and CE.

H3: There is a positive and significant relationship between TIC and CEP.

TIC influences the changing relationship between SCDO and CEP. Another TIC that firms can use is the concept of blockchain technology (BCT). The BCT serves as permanent information storage having high and strict security. Using the concept of BCT, each report is shared. Therefore, all data is accessed by authorised networks in the chain. The BCT, as technological innovation, can make the transaction transparent and free from manipulation (Lu, 2018). According to Lu (2018), the relationship between BCT and CEP could prevent interference. Therefore, BCT's use will help integrate and share information throughout the SC process. In addition, BCT has the advantage of offering strict security of online communication. The technology can inform the users and enhance the SC integration and cooperation among the networks (Alnajem et al., 2021; Rusinek, 2018). Also, through past supply chain disruptions orientation, firms began to use BCT and CEP to change company security system patterns to protect the organisations' intellectual property (Kouhizadeh, 2019).

H4a: TIC mediates the relationship between SCDO and CEP.

The introduction of the IR4.0 era to support operations of Third-party logistics (3PLs), has improved information and automated systems' accuracy and speed to provide better data capture. New techniques include Electronic Logging Devices (ELDs) to obtain proprietary information such as employee feedback on supply chain management and CEP. Throughput

ELD is used to control the response to operations and reduce risks and problems. However, with limited technology resources to support CEP's implementation, small and medium enterprises need to be better prepared for technology disruption (Bui et al., 2021; Soroka, 2017). Thus, the Malaysian government has created a comprehensive business model designed to reduce costs and create legitimacy (Manninen, 2018). After that, IR 4.0 and CEP have an integration that can help the industry transform traditional linear SC to CEP or closed loop. In addition, it reduces the waste of material and resource use in SC (Jabbour, 2018).

H4b: TIC mediates the relationship between MSCD and CEP.

According to Bode (2018), firms can make initial preparations as a backup, like the problem of stuck material resources and delay risk that leads to supply chain disruption. This study argues that the deployment of TIC could quickly resolve discretion issues. The IR4.0 is an interference platform to monitor potential disruption and early warning detection systems. The firms can adopt a supply chain disruption strategy to support CE practices and improve the CEP. The recovery phase needs to ensure the CE process is stable and sustainable. Nayal et al. (2021) argued that the IR4.0 related technologies such as Artificial Intelligence and the Internet of Things mediate the supply chain and firm performance under the CE. The technology has driven the mitigating supply chain disruption discovery, and the response stage has a mediating role on the firm’s readiness prior to a disruption (Bode & Macdonald, 2017).

H4c: TIC mediates the relationship between SCDD and CEP.

3. Methods

The data were collected using a quantitative technique with a set of questionnaires. This method was selected to obtain a more dispersed location of respondents with accurate information. To ensure the accuracy of statistical results, the early response and late response tests were examined. There was no reaction bias found to exist between these data-collection approaches. This study used IBM SPSS 26 to examine the sample profile and PLS-SEM with SmartPLS version 3.3.8 to calculate convergent and discriminant validity, composite reliability, and PLSpredict. The measurement items were adapted from the previous studies (Table 2) and verified and tested using a pilot test. The pilot test was conducted among 30 practitioners, and the results were not included for final analysis (α = >80). The feedback from the pilot test was the questionnaire needed to be amended with minor language concerns and each of exogenous and endogenous variables.

Figure 1 shows the research process that starts with the problem identification from the previous literature. The literature has been utilised to develop a theoretical framework and hypothesis development. The variables and research instruments have been identified to survey manufacturing firms. Thus, we have collected the data and analysed using three different software. First is IBM SPSS 26 to analyse the respondent profile and descriptive statistics. Next, we have utilised WrapPLS 7.0 to test the common method bias. Then the survey data was examined to ensure the research model was valid and reliable. The measurement model and hypothesis testing have been examined using PLS-SEM with PLSPredict as the features for better model prediction. We have presented results and discussed them in the discussion section, followed by a conclusion and suggestions for future research. The details of the research procedure were discussed in the following subsections.

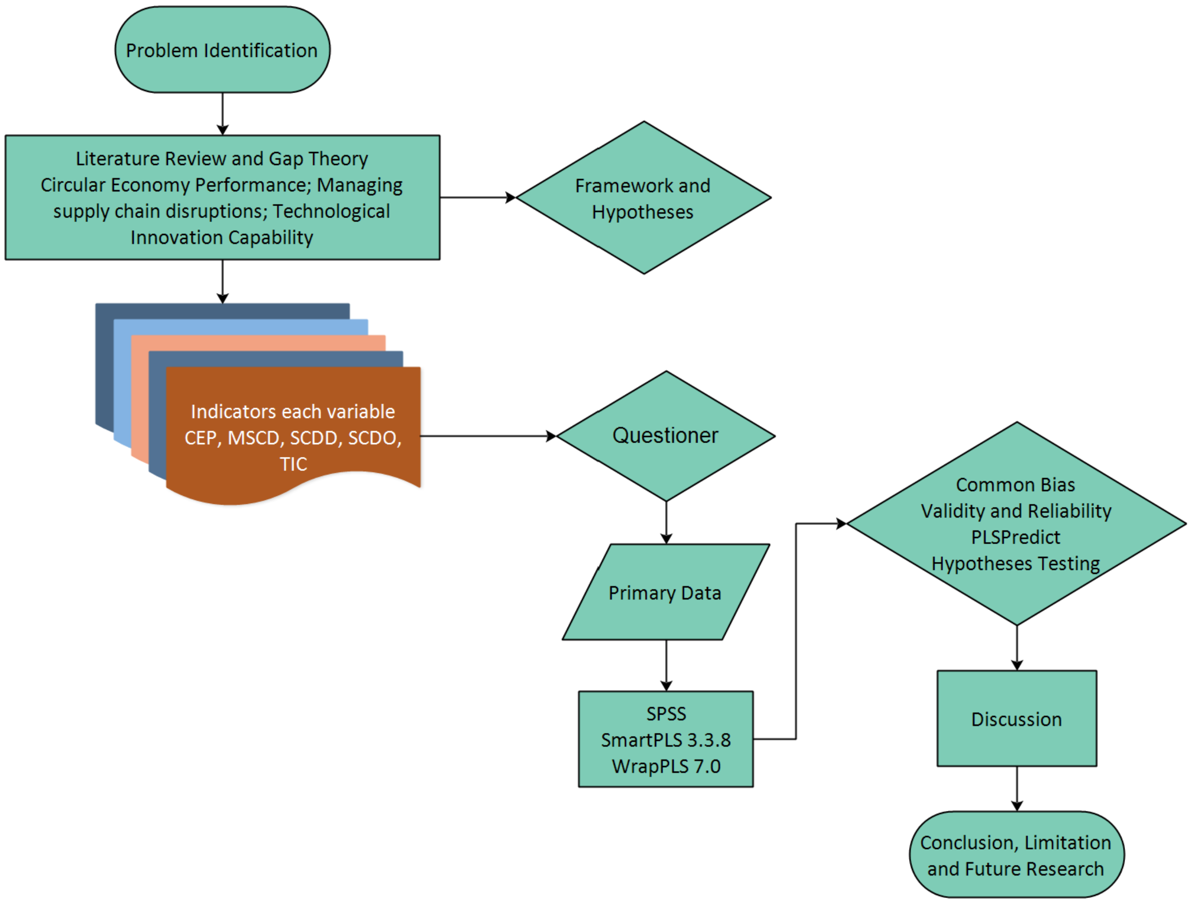

Figure 1: Research process

3.1. Sampling and data collection

Based on Federal Malaysia Manufacturers (FMM) directory (2021), the relevant firms in this study were identified (*N*=700). This study has targeted manufacturing firms that deployed IR4.0 technology and practised a CE. This study argues that those targeted companies have been involved in IR4.0 adoption and have the knowledge and experience to overcome the environmental issues using the CE concept. There are two filter questions in the survey to ensure only those companies involved in IR4.0 and the CE can participate in the survey. The set of the questionnaire was targeted to the managerial level such as top management, chief executive officer, manager officer, and senior manager. A second reminder is sent via email for companies that do not respond within a week. This second reminder for late response is sent because most Malaysian companies are more focused on reviving the company's economy during the COVID-19 pandemic. Also, the study sample used G-Power software with a required minimum of 119 respondents in the model. A stratified random sampling technique was deployed to collect the data, which is a sampling method that divides the population into smaller subgroups known as strata. The top management has been identified as the strata (Fernando & Wah, 2017).

This study has distributed 700 questionnaires to companies registered under the Federation of Malaysian Manufacturers (FMM). Based on the questionnaire distributed, only 130 respondents responded to the questionnaire, and 570 respondents did not respond. Most of these respondents are top management, chief executive officers, managing officers, and senior managers of companies in the manufacturing industry. The cut-off value of participation was one week after the first request to participate in the survey. For companies that do not respond within a week (early response), a second reminder (late response) was sent with another two weeks of timeframe. The data collection was stopped for four weeks, and a test of non-response bias was conducted. It is argued that there is not enough evidence to conclude the non-response bias exists in the model (p-value>0.05).

3.2. PLS-SEM Analysis

Our study uses PLS-SEM analysis because of its flexible technique for modelling the research constructs (Henseler, 2010). There are a few justifications to utilise PLS-SEM as a multivariate statistical technique. First, the PLS-SEM can visualise the relationship among variables and statistically test the validation of the model. Second, PLS-SEM has suitable for variance-based relationships. Sarstedt et al. (2017) and Hair Jr et al. (2017) argued that PLS-SEM has integrated factor analysis techniques and multiple regression that can be used to test the model fit and hypothesis testing simultaneously. PLS-SEM has gained popularity because of its ability to test the complex model using a variance-based SEM approach. Finally, our study has predicted the accuracy of enablers of CEP using PLSPredict. We argue that PLS-SEM with PLSPredict feature fits to answer our research objectives.

In PLS-SEM, there are two measurement models, namely the outer model and the inner model. The outer model is measured using an algorithm approach, while the inner model is measured by bootstrapping. The output of the outer model is utilised to assess the goodness of the data, such as convergent and discriminant validity. The convergent validity test refers to the standardised loading factor and Average Variance Extracted (*AVE*) values, while the discriminant validity uses the Fornell-Larker Criterion approach and the HTMT ratio. Internal consistency testing uses Cronbach Alpha (*CA*) and Composite Reliability (CR). All model measurements are reflective. Next, testing the inner model for the evaluation of the structural model. The outputs of the inner model include R-Square (R^2), F-Square (f^2 – effect size), Q-Square – predictive relevance (Q^2) with the PLSPredict approach (which will be explained later in a special section) and path coefficient values along with their values. Significance (Sig and *t*-value). We have tested the inner and outer models using the PLS-SEM 3.3.8.

3.3. Validity and Reliability Analysis

In this study, PLS-SEM 3.3.8 was used as a tool to test the theoretical hypothesis. Prior to the hypothesis testing, the model's goodness was deployed, including convergent validity, discriminant validity, and validity of measurement indicator. PLS-SEM version 3.3.8 was used to measure the data quality, structural measurement, and intervention effect. This study will report the value for convergent validity, discriminatory validity, and reliability for the data's quality. Also, the PLS Algorithm method is used to obtain convergent and discriminant validity values. The study obtained the necessary data through this method, such as CR. The composite reliability or construct reliability also measures internal consistency in scale items.

3.4. PLSpredict

Hair et al. (1984) suggested using the holdout sample approach to assess out-of-sample predictive power in multivariate methods. Still, this technique was less popular because of the limited support software to conduct the analysis. Currently, SmartPLS 3.3.8 provides a facility to calculate the predictive power of the holdout sample. It was proposed by Shmueli (2016) using the PLSpredict procedure. PLSpredict uses the holdout sample method to generate predictions for observational (item/indicator) (Shmueli, 2019). PLS-SEM's R-Square and Q-

Square measures are in-sample predictions, but PLSpredict uses several randomly selected holdout samples to calculate out-of-sample predictive power (Hair, 2021). In this study, predictive validity was carried out using the PLS-predict procedure, which refers to cross-validation with a holdout sample (Felipe, 2017; García-Fernandez, 2018; Shmueli et al., 2016). This technique aims to produce a more accurate predictive performance assessment of the exogenous variables of CEP and TIC (Cepeda Carrion, 2016).

4. Results

A total of 700 questionnaires were distributed to expand the number of respondents. This study used the reference directory of FMM 2021.

4.1. Profile of manufacturing firms

FMM brings more than 3200 registered manufacturing and service firms. Through this study, 130 legitimate manufacturing firms are ISO 14001 certified, adopt IR4.0 in supply chain management, and have a direct COVID-19 Pandemic impact on the company's economy. The highest participation in this survey was from chemical manufacturing (28%), while other sectors have a relatively similar distribution. Besides, 130 respondents who have ISO 14001 in the company are significant because ISO 14001 is an industry-standard framework that plans organisations to establish an effective environmental management system. Therefore, it has a positive effect on the environment in the future. The majority of the Industry 4.0 technology deployment to manage industrial waste was the IoT at (29.5%), followed by cloud computing at (22.7%) and the lowest is an augmented reality at (3%). Also, the highest contribution activity for financial saving was from remanufacturing at (19.7%). The production manager (28.8%) has the main contributors to the survey. Table 1 shows a summary profile of manufacturing firms.

Table 1: Profile of manufacturing firms

Demographic Variables	Description	Frequency	Valid Percent (%)
ISO 14001 certification	Yes	130	100%
	No	0	0%
Adopt IR4.0 in supply chain management	Yes	130	100%
	No	0	0%
	Reduce unnecessarily	19	14.4%
	Re-use	17	12.9%
Most contribute activity for financial saving	Recycle	33	25%
	Redesign	11	8.3%
	Remanufacturing	26	19.7%
	Refurbish	10	7.6%
	Recover	14	10.6%
	Big Data	27	20.5%
Type of IR4.0 technology to manage industrial waste	Artificial Intelligence	20	15.2%
	Internet of things	39	29.5%
	Cloud Computing	30	22.7%
	Augmented Reality	4	3%
	Additive Manufacture	10	7.6%
	Textile manufacturing	6	4.5%
	Apparel manufacturing	3	2.3%
	Leather and allied product manufacturing	2	1.5%
	Wood product manufacturing	2	1.5%
Type of manufacturing industry	Paper manufacturing	3	2.3%
	Petroleum and coal manufacturing	3	2.3%
	Chemical manufacturing	37	28%
	Plastics and rubbers manufacturing	25	18.9%
	Metal manufacturing	5	3.8%
	Machinery manufacturing	7	5.3%
	Computer and electronics manufacturing	30	22.7%
	Furniture manufacturing	4	3%
	Other	3	2.3%
Position in the company	Production Manager	38	28.8%

	Supply Chain Management/ Logistic Manager	25	18.9%
	Chief Executive Officer/ Managing Director	20	15.2%
	Civil Engineering Supervisor	4	3%
	Health and Safety Manager	32	24.2%
	Senior Engineer	4	3%
	Senior Manager	4	3%
	IT Manager	3	2.3%

4.2. Common methods variance (CMV)

Fernando and wah (2017) argued that the CMV is a necessary test to avoid the detrimental effects of method bias. Typically, the CMV needs to be handled carefully in the survey-based method to ensure the model assessment quality and hypothesis testing. The CMV usually exists because of systematic error variance in the research model since the exogenous and endogenous data were collected at one point (a cross-sectional study). We have conducted the full collinearity variance inflation factor (FCVIF) assessment method to identify the CMV issue in the model (Kock, 2015; 2021). In PLS-SEM, the latent variable was calculated based on the aggregation of indicators. As a result, variance inflation factors (VIFs) are generated for all latent variables in the model. We computed FCVIF for both inner and outer models using WarpPLS 7.0. We found results of full collinearity for all of the exogenous and endogenous variables below the cut-off value (VIF ≤ 3.3). Therefore, we conclude that there is no evidence to claim the CMV issue exists in our research model (Table 2).

Tabel 2: Results of Full collinearity VIF

Statistical technique	MSCD	SCDO	SCDD	TIC	CEP
Full collinearity VIF (FCVIF)	2.031	3.197	3.143	2.408	2.846

4.3. Convergent Validity and Descriptive Statistics

Table 3 shows the four factors assessed in this study: mean indicator, factor loadings (FL), CR, and AVE. All FL values are higher than 0.7. Therefore, to establish the convergent validity, CR needs to be higher than 0.7. We found that CR values ranged from 0.893 to 0.947, which met the cut-off threshold value. Meanwhile, the AVE has met the required condition with more than 0.5, and the values ranged from 0.579 to 0.795. The internal consistency was measured using the CA test, and the results ranged from 0.850 to 0.929. The results of descriptive analysis, the overall evaluation of CEP has a mean value = 3.877; SD=0.081 and mean value for SCDD =3.887; SD=0.081. MSCD =4.019; SD=0.080 were evaluated with slightly better mean value scores with others, and SCDO were evaluated with mean=3.798; SD=0.100. Also, TIC has mean value = 3.948; SD=0.079. We have concluded that our data fulfilled the convergent validity requirements.

Table 3: Result of Reflective Measurement Model and Descriptive Statistics

Variable	Item	Mean	SD	FL	AVE	CR
CEP SD=0.081 Mean=3.877 CA = 0.872	CEP1. Our company has recycled more than the total usage of raw material	3.915	3.923	0.709	0.611	0.904
	CEP2. Our company has produced more detachable products.	3.985	3.992	0.774		
	CEP3. Our company has increased reusable function for our final products	3.877	3.892	0.845		
	CEP4. Our company has increased the recyclable function of our final products	3.915	3.915	0.785		

Variable	Item	Mean	SD	FL	AVE	CR
	CEP5. Our company has increased the re-use of rejected products for the production process	3.738	3.738	0.737		
	CEP6. Our company has increased re-use waste for the production process.	3.892	3.908	0.833		
SCDD SD=0.080 Mean=4.019 CA = 0.912	SCDD1. Our company supply chain system enables us to evaluate which process is exposed to supply chain disruption	3.908	3.877	0.784	0.795	0.939
	SCDD2. Our company set up alternative plans associated with identified risks	4.085	4.054	0.916		
	SCDD3. Our company can evaluate the accuracy of the information that has come to our company	4.015	3.977	0.921		
	SCDD4. All parties that are involved in our supply chain help us to increase visibility to observe supply chain disruption	4.069	4.046	0.937		
MSCD SD=0.100 Mean=3.798 CA = 0.929	MSCD1. Our company has a mitigation plan for our logistics	3.846	3.808	0.921	0.783	0.947
	MSCD2. Our company always enhances monitoring activity on supply chain disruption	3.877	3.831	0.806		
	MSCD3. Our company faced minimal disruption on supply chain	3.623	3.631	0.816		
	MSCD4. Our company has various ideas to prevent disruption on our supply chain	3.815	3.785	0.934		
	MSCD5. Our company often takes corrective steps after a disruption has occurred	3.831	3.800	0.938		
SCDO SD=0.079 Mean=3.948 CA = 0.878	SCDO1. Our company is always alert to any potential supply chain disruption at any time	4.000	3.985	0.760	0.579	0.905
	SCDO2. Our company notices that supply chain disruption is impending	3.869	3.854	0.761		
	SCDO3. Our company consistently monitors how our	3.962	3.946	0.788		

Variable	Item	Mean	SD	FL	AVE	CR
	supply chain can avoid disruption					
	SCDO4. Our company have a proper parameter to prevent disruption from occurring	3.862	3.862	0.725		
	SCDO5. Our company always give training to our employee to overcome supply chain disruption	4.008	4.000	0.742		
	SCDO6. Our company have a dedicated response team to mitigate damage brought by supply chain disruption.	4.062	4.038	0.703		
	SCDO7. Our company have a proper parameter to prevent disruption from happening.	3.877	3.869	0.837		
TIC SD=0.087 Mean=3.905 CA = 0.850	TIC1. Our company has adequate technical know-how on IR4.0 to support our operational activities	3.946	3.931	0.799	0.627	0.893
	TIC2. Our company has the capability to utilise technological information efficiently	4.000	3.985	0.781		
	TIC3. Our company has the technological capability to utilise advanced equipment for IR4.0 manufacturing systems	3.954	3.931	0.884		
	TIC4. Our company has sufficient resources to manage the technological change based IR4.0 requirements	3.808	3.777	0.743		
	TIC5. Our company has the technological capability to develop green products or processes	3.815	3.800	0.742		

Note: SD = standard deviation; adapted measurement items (CEP = Gusmerotti et al., 2019 ; SCDD = Brusset and Teller, 2017 ; MSCD = Revilla and Sáenz, 2014 ; SCDO = Yu et al., 2019 ; TIC = Lall, 1996).

4.4. Construct Validity

In PLS-SEM, the result of the theoretical framework is presented in Figure 2. In this PLS-Path Model, factor loading ranges from 0.709 to 0.956 for all the indicators. Based on the Modified PLS-Path Model, some of the measurement items have factor loadings less than 0.5, which are suggested to be deleted from the model, which is SCO1 and SCO5. It ensures that a set of measures (manifest variable) represent the theoretical latent variable (Hair, 2011). As presented, this type of validity was assessed by using convergent and discriminant validity.

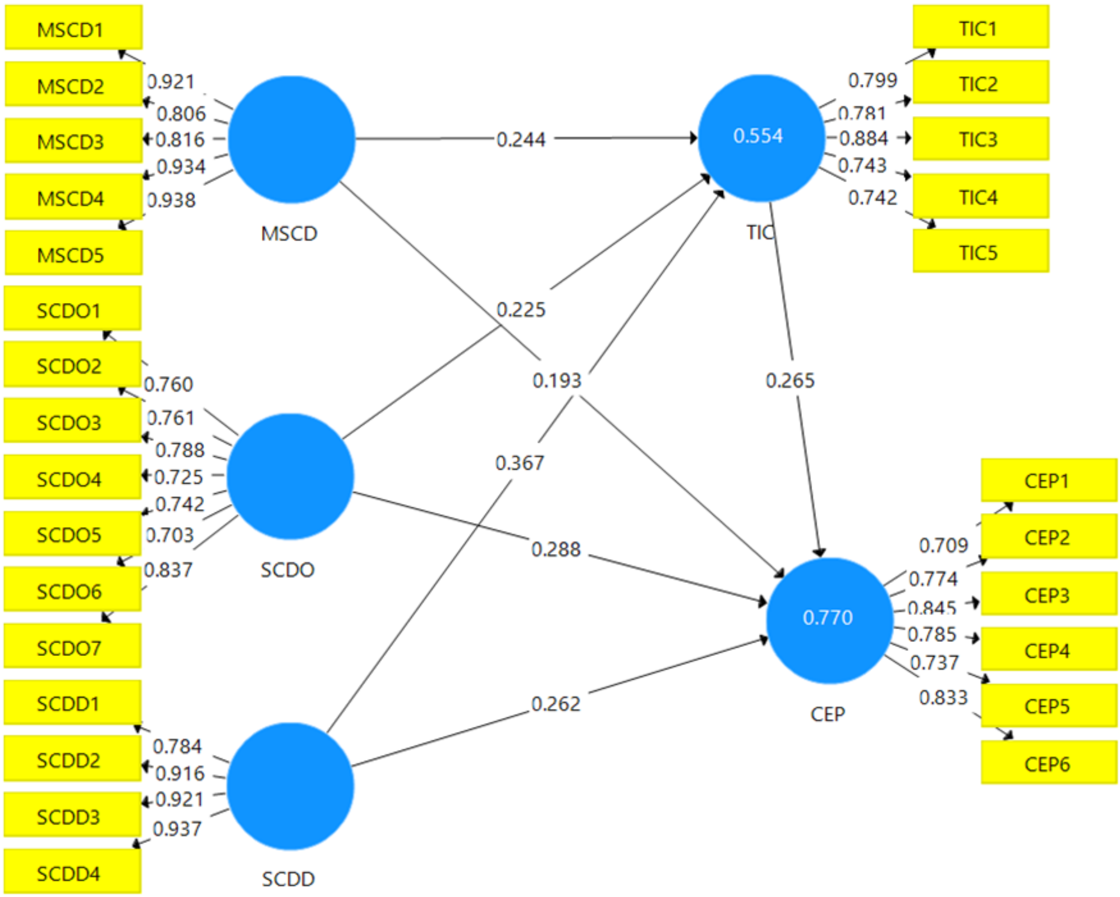

Figure 2: Theoretical framework based on PLS-SEM

This study also used construct validity to determine whether all items used were valid. The cut-off value greater than 0.7 is generated and applied to the significant loading. The value that is considered greater than 0.5 in two or more factors of any item is contemplated to have notable cross-loading. Within their own construct, their independent items are each highly loaded. The construct is considered acceptable when the value of the main loadings is higher than the values of the cross-loading. Table 5 shows the result of standardised loadings and cross-loadings.

Table 5: Standardised loadings and cross-loadings

	CEP	MSCD	SCDD	SCDO	TIC
CEP1	**0.709**	0.489	0.518	0.525	0.437
CEP2	**0.774**	0.640	0.642	0.686	0.651
CEP3	**0.845**	0.535	0.646	0.656	0.662
CEP4	**0.785**	0.503	0.650	0.656	0.591
CEP5	**0.737**	0.597	0.595	0.515	0.506
CEP6	**0.833**	0.524	0.627	0.658	0.666
MSCD1	0.628	**0.921**	0.515	0.591	0.555
MSCD2	0.620	**0.806**	0.576	0.542	0.485
MSCD3	0.615	**0.816**	0.540	0.532	0.580
MSCD4	0.602	**0.934**	0.523	0.598	0.519
MSCD5	0.634	**0.938**	0.549	0.589	0.567

	CEP	MSCD	SCDD	SCDO	TIC
SCDD1	0.714	0.452	**0.784**	0.731	0.602
SCDD2	0.691	0.564	**0.916**	0.677	0.607
SCDD3	0.682	0.606	**0.921**	0.667	0.612
SCDD4	0.713	0.555	**0.937**	0.696	0.638
SCDO1	0.635	0.564	0.693	**0.760**	0.524
SCDO2	0.569	0.500	0.549	**0.761**	0.379
SCDO3	0.639	0.616	0.661	**0.788**	0.577
SCDO4	0.627	0.433	0.542	**0.725**	0.467
SCDO5	0.558	0.420	0.542	**0.742**	0.578
SCDO6	0.499	0.288	0.458	**0.703**	0.429
SCDO7	0.673	0.569	0.665	**0.837**	0.568
TIC1	0.599	0.464	0.570	0.537	**0.799**
TIC2	0.577	0.491	0.551	0.524	**0.781**
TIC3	0.684	0.524	0.630	0.640	**0.884**
TIC4	0.606	0.530	0.509	0.493	**0.743**
TIC5	0.514	0.412	0.459	0.428	**0.742**

4.5. Discriminant Validity

The Heterotrait-Monotrait ratio (HTMT) served to measure the similarity between the variables. It is argued that the discriminant validity has been set if the calculation of HTMT is less than one (Franke & Sarstedt, 2019). Besides, the cross-loading and Fornell Larcker criterion is unable to test the discrimination statistically. However, the Fornell Larcker criterion does not depend on inference statistics. According to Henseler et al. (2015), the solution proposes to use HTMT criteria to measure and evaluate discriminatory validity alternatives. The complete result of the discriminant validity assessment (Fornell-Larker Criterion) is presented in Table 6. Table 7 shows the average variants extracted and the correlation amongst the variables. It was found that all constructs' square correlation is smaller than the average variance of the square root obtained from measurement items. Table 7 also indicates the result of the HTMT criterion test. Since all values of the HTMT criterion are below 0.90, discriminant validity is established. Therefore, the discriminant validity is also confirmed and appropriate for hypothesis testing.

Table 6: Discriminant validity of constructs (Fornell-Larker Criterion).

	CEP	SCDD	MSCD	SCDO	TIC
CEP	0.782				
SCDD	0.787	0.891			
MSCD	0.702	0.612	0.885		
SCDO	0.793	0.779	0.646	0.761	
TIC	0.757	0.691	0.614	0.668	0.792

Table 7: Result of Heterotrait-Monotrait (HTMT) criterion for discriminant validity

	CEP	SCDD	MSCD	SCDO	TIC
CEP					
DD	0.880				
SCD	0.780	0.666			
SCO	0.897	0.863	0.706		

TIC	0.868	0.782	0.689	0.761	

4.6. PLSpredict

The Q-Square value is positive for constructs endogen predictions (Table 8). Thus, the PLS-SEM model presents a suitable predictive performance. To predict the endogen indicators, a comparison of the results of the PLS and the linear model (LM) was carried out (Table 8). As a result, the difference in the PLS-SEM (PLS-Predict) value with the LM regression means (LM-Predict) for the root mean squared error (RMSE) and the mean absolute error (MAE) was negative. Thus, the values were close to zero. Based on these results, the proposed model with PLS has a slight increase in the predictive relevance of the indicator data (García-Fernandez et al., 2018). The result of the Q-Square prediction is a difference with a positive value or close to zero. PLS-SEM has slightly better predictions than LM regression (Felipe et al., 2017). Hair et al. (2019) proposed that if the PLS-SEM results are smaller than the LM for all indicators, then the indicators on endogenous variables have high predictive power. Given the predictive power of the results, this study offers additional support in terms of stability.

Table 8: PLSpredict Assessment

		PLS-Predict			LM-Predict			PLS-LM		
Variable	Indicator	RMSE	MAE	Q^2-predict	RMSE	MAE	Q^2-predict	RMSE	MAE	**Q^2-predict**
Circular Economy Performance (CEP)	CEP1	0.635	0.502	0.315	0.679	0.538	0.215	-0.044	-0.036	**0.100**
	CEP2	0.509	0.385	0.519	0.519	0.398	0.501	-0.010	-0.013	**0.018**
	CEP3	0.529	0.406	0.462	0.565	0.422	0.387	-0.036	-0.016	**0.075**
	CEP4	0.573	0.413	0.451	0.660	0.463	0.272	-0.087	-0.050	**0.179**
	CEP5	0.607	0.505	0.391	0.675	0.505	0.245	-0.068	0.000	**0.146**
	CEP6	0.561	0.409	0.449	0.626	0.460	0.315	-0.065	-0.051	**0.134**
Technological Innovation Capability (TIC)	TIC1	0.562	0.428	0.331	0.574	0.441	0.301	-0.012	-0.013	**0.030**
	TIC2	0.554	0.419	0.324	0.572	0.451	0.280	-0.018	-0.032	**0.044**
	TIC3	0.492	0.369	0.431	0.529	0.412	0.342	-0.037	-0.043	**0.089**
	TIC4	0.650	0.486	0.313	0.721	0.536	0.156	-0.071	-0.050	**0.157**
	TIC5	0.612	0.477	0.214	0.679	0.508	0.030	-0.067	-0.031	**0.184**

Q^2-Predict of CEP = 0.720; Q^2-predict of TIC = 0.525

4.7. Structural Model Assessment

This study has utilised bootstrapping technique to examine the hypothesis decision. The function of bootstrapping is to test the statistical significance of various PLS-SEM results such as *t*-value, *p*-value, path coefficients, and standard deviation. The bootstrapping application for mediation analysis has recently been suggested by Hair et al. (2011). In addition, we have evaluated R^2 and f^2 values based on the process of the structural model algorithm. We also identify each variable's direct and indirect effects using the bootstrapping procedure. Next, the direct effect's cut-off t-value is greater than 1.645 for the one-tailed test and greater than 1.96 for the two-tailed indirect effect. The p-value cut-off is less than 0.05, which means a substantial relationship exists between the two domains. The direct and indirect effects decisions are shown in Table 9 for ten Path coefficients (Direct Effect) and Table 10 for three Path coefficients (Indirect Effect).

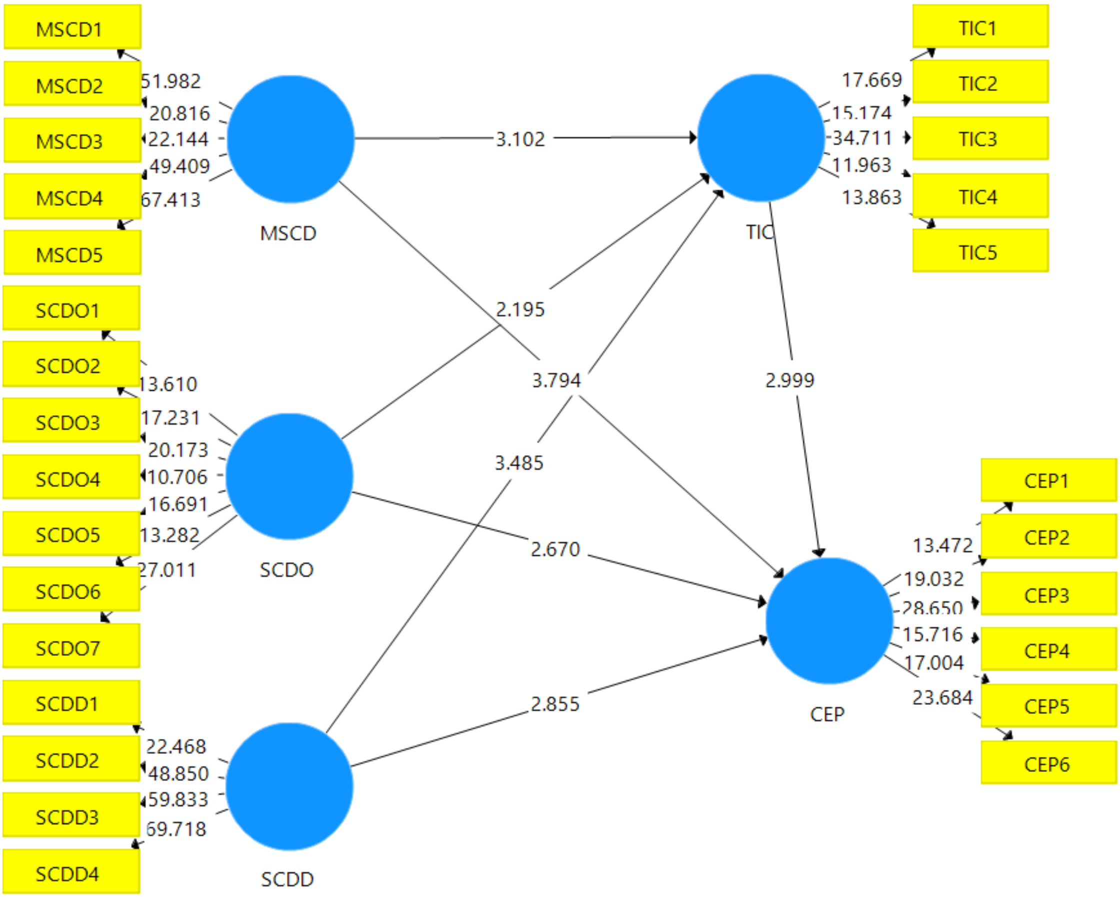

Figure 3. Hypotheses Testing (Bootstrapping Methods)

Table 7: Ten path coefficients (Direct Effect)

Hypothesis	Path	STD	SD	R^2	f^2	Confidence Intervals Bias Corrected: Bias	2.5%	97.5%	*t*-Statistics	*p*-values	Decision
H1a	SCDO -> TIC	0.225	0.103		0.039	0.008	0.008	0.416	2.195	0.029	Support
H1b	MSCD -> TIC	0.244	0.079		0.074	-0.005	0.086	0.387	3.102	0.002	Support
H1c	SCDD -> TIC	0.367	0.105	0.554	0.112	-0.003	0.146	0.556	3.485	0.001	Support
H2a	SCDO -> CEP	0.288	0.108		0.120	-0.003	0.089	0.505	2.670	0.008	Support
H2b	MSCD -> CEP	0.193	0.051		0.084	-0.004	0.091	0.294	3.794	0.000	Support
H2c	SCDD -> CEP	0.262	0.092		0.100	0.003	0.090	0.452	2.855	0.004	Support
H3	TIC -> CEP	0.265	0.088	0.770	0.136	0.005	0.093	0.435	2.999	0.003	Support

Note: SCDO = Supply chain disruption orientation; MSCD = Managing supply chain disruption; SCDD = Supply chain disruption recovery; TIC = Technological innovation capability; CEP = Circular economy performance; Accepted if the t-value is > 1.645 and p-value < 0.05

Table 8: Path coefficients (Indirect Effect Testing)

Hypothesis	Path Direct and Indirect	STD	SD	Confidence Intervals Bias Corrected: Bias	2.50%	97.50%	*t*-Statistics	*p*-values	Decision
H4a	SCDO -> TIC -> CEP	0.060	0.034	0.003	0.007	0.137	1.748	0.081	Direct-only non-mediation
	SCDO -> TIC			0.008	0.008	0.416			(No Support)
	TIC -> CEP			0.005	0.093	0.435			
	SCDO-> CEP			-0.003	0.089	0.505			
H4b	MSCD -> TIC -> CEP	0.065	0.032	0.000	0.018	0.150	2.034	0.043	Complimentary Mediation
	MSCD -> TIC			-0.005	0.086	0.387			(Support)
	TIC -> CEP			0.005	0.093	0.435			
	MSCD -> CEP			-0.004	0.091	0.294			
H4c	SCDD -> TIC -> CEP	0.097	0.046	0.001	0.029	0.223	2.121	0.034	Complimentary Mediation
	SCDD -> TIC			-0.003	0.146	0.556			(Support)
	TIC -> CEP			0.005	0.093	0.435			
	SCDD -> CEP			0.003	0.090	0.452			

Note: SCDO = Supply chain disruption orientation; MSCD = Managing supply chain disruption; SCDD = Supply chain disruption recovery; TIC = Technological innovation capability; CEP = Circular economy performance; Accepted if the t-value is > 1.645 and p-value < 0.05.

4.7. Results of Hypothesis Testing

This section will discuss the result of hypothesis testing using PLS-SEM software through PLS bootstrapping (Figure 3). The R^2 value of CEP is 0.770, meaning that 77% of the variance is explained by supply chain disruption discovery, and the R-square value of TIC of 0.554 indicates that SCDO, MSCD and SCDD can explain 55.4% of the variance. Our R^2 value has intermediate and substantial strength since the thumb rule is 0.25 for low, 0.5 for intermediate, and 0.75 for substantial for an acceptable R^2 deal (Hair et al., 2014).

Our main hypothesis predicts that CEP will have a positive relationship with SCDO, MSCD, SCDD, and TIC. There are ten hypothesis testing outcomes from this study. H1a (*t*-value=2.195; *p*-value = 0.029), H1b (*t*-value = 3.102; *p*-value = 0.002), and H1c (*t*-value = 3.485; *p*-value = 0.001) which predict the influences of SCDO, MSCD and SCDD, respectively, are related to TIC and it is found that H1a-H1c are significant (accepted) at *p*-value (<0.05). Also, H2a (*t*-value=2.670; *p*-value = 0.008), H2b (*t*-value=3.794; *p*-value = 0.000), and H2c (*t*-value=2.855; p-value = 0.004) are significant at p-value (<0.05). Next, H3 proposes that TIC is positively related to CEP and was found significant at p-value below 0.05 (*t*-value=2.9995; *p*-value = 0.003).

Lastly, the results confirmed that TIC non-consistently mediates the relationship between SCDO and CEP. The mediating procedure has followed the procedure of Zhou et al. (2010). It is argued that when the indirect effect (SCDO -> TIC -> CEP) was not significant and positive (*b4a*=0.060; *p*-value=0.081), the direct effect indicates significant and positive. We argued that when this condition exists, it needs to be categorised as a direct-only non-mediation. This study argues that because the direct effect is significant and positive, the possibility to omit mediator exists in the research model. We found that the relationship path on SCDO -> TIC -> CEP is direct-only. It is concluded that the H4a statement did not support mediation. When both the indirect effect and direct effect between MSCD -> TIC -> CEP is significant and positive (*b4b*=0.065; *p*-value=0.043), it is called complementary (partial mediation). The H4b statement was supported mediation. Furthermore, when both the indirect effect and direct effect between SCDD -> TIC -> CEP is significant and positive (*b4c*=0.097; *p*-value=0.034), it is called complementary (partial mediation). The H4c statement was supported mediation. All mediation test results are summarised in Table 8.

5. Discussion

The aims of this study are twofold. The first aim is to answer whether Industry 4.0-driven manufacturing firms have a proper mitigation strategy to avoid technological disruption in adopting the circular economy practices. This study also has answered the mediating role of TIC in mitigating the IR4.0 disruption in the manufacturing industry. In order to answer the first objective, this study has examined the direct path between exogenous and endogenous variables. Our findings found that supply chain disruption management has significantly influenced TIC. It means that manufacturing firms are better technological prepared with cyber risk mitigation plans in the supply chain. In addition, manufacturing firms have the ability to use IR4.0 technology to predict what cyber turbulence will occur.

Small, medium-sized manufacturing firms must also prepare themselves for negative effects because there is not enough technology and expertise to handle the IR4.0 disruption. Our findings align with Trkman and McCormack (2009) that firms need to invest in a supplier development programme to anticipate the turbulence or other external factor changes that do not fit within the SC strategy. The supply chain disruption can come from the suppliers and external factors. Besides being vital to managing supply chain disruption, post-recovery also play a significant role. Our findings confirmed that the technological capability has contributed to rapid supply chain disruption recovery. IR4.0 technology and digital transformation can assist manufacturing firms to recover when warehouse and production lines are fully automated. It does not necessarily need physical intervention to handle recovery. Chen et al. (2021) has supported our findings that argued that the manufacturing could change alternative suppliers to supply raw materials or quickly change the product type partly.

The results found that managing supply chain disruption significant impacts CEP. Supply chain disruption is unprecedented. Therefore, the manufacturing firms need to have a contingency recovery strategy. Gaustad et al. (2018) have supported our finding that materials supply has become less diverse. Therefore, the manufacturer needs to classify the type of materials accordingly. For example, by using the circular economy practices to recycle, remanufacture, re-use scrap or end life products. The circular economy-based materials can assist manufacturing firms with materials availability and ensure that materials supply is sufficient for production and consumption.

Loss of profit is a threat to manufacturing firms when a supply chain disruption occurs. This is because the firm does not have enough technological capability to recover. Other than that, Gaustad et al. (2018) argued that socioeconomic factors make the supply chain become vulnerable. The significance of IR4.0 technology's role is to assist firms with automation when a global pandemic strikes the industrial sector. Our study found that technological innovation has positively mediated managing supply chain disruption, recovery and CEP. Our finding is in line with Getor et al. (2020), who argued that integrating TIC and circular economy benefits the economy and the country's environmental well-being.

The innovative technology becomes an alternative to the firm to take care of the environment. Besides, in IR4.0, there are several advantages of IR4.0 with TIC and CE. For example, IR4.0 contributes to the sustainability and efficiency of CEP using the IoT and Internet of service to connect industries through external and internal SC networks electronically (Oláh et al., 2020). Also, recycling resources capable of minimising waste of resources and implementing IR4.0 in the CE have positive effects (Angioletti et al., 2017), such as producing more quality and innovative products in the future.

Our finding indicates that TIC does not significantly contribute as mediating variable to connect supply chain disruption orientation and circular economy performance. However, a lack of understanding and experience in supply chain disruption orientation and IR4.0 has led to no insignificant results. According to Stet et al. (2014), the use of technology innovation in the supply chain should not harm firm performance. But when it is not appropriately managed, the misuse of innovative technology can lead to hackers' theft of confidential data, and the automation is run remotely. There are also some other disadvantages, such as allowing third parties to access data in the supply chain, which is a high risk of data commercialisation to unauthorised parties.

6. Conclusion

This study provides insight to integrate the technological innovation capabilities with IR4.0 to assist the manufacturing firm for supply chain recovery. Based on our discussion of findings, we have provided three types of implications. The first implication is to the theory and scholars. Our study has extended ecological modernisation theory that assists the firms in designing the digitalisation strategy, and IR4.0 technology has driven innovation for circular supply chain and performance improvement. We suggest that the risk management capability need to be incorporated in the ecological modernisation theory and ensure that risk factor can be managed. Our study has filled the current research gaps that limited empirical studies examined the mediating role of technological innovation on the relationship between supply chain disruption and CEP. IR4.0 is also widely discussed in the CE literature but debated separately on how the CEP is improved using technological innovation.

The second implication is for industry and practitioners. The results of this study can assist the manufacturing firms to understand how to mitigate the IR4.0 disruption strategy that focuses on the CEP. The circular economy can overcome the materials challenges issue of increasing the cost of material resources, which struck at the core of the global value chain hub and disrupted production due to the COVID-19 pandemic. This study reveals advantages of CE to manufacturing firms, such as reducing the dependence on imported materials, especially during pandemic COVID-19. In addition, the firms can increase exposure and awareness to use the latest technology innovation through three approaches: assets, process, and ability.

The third implication is for policymakers. We suggest that the government design a waste management policy incorporating circular economy practices. A circular economy system can also reduce waste by reusing or recycling and remanufacturing waste, leading to business sustainability. Through this system, manufacturing firms can directly work with the government agency to curb severe waste problems. We also suggest that the IR4.0 policy be strengthened and provide clear guidance to comply with a global data-sharing standard (Fernando et al., 2022c). We also urge that the government encourage the industry to push the IR4.0 technology adoption and provide an incentive for the success of the implementation of circular economy and benefit the society. Adopting a circular supply chain based on IR4.0 accelerates the digital economy's growth.

Our study has acknowledged the limitation, such as limited access to retrieve the actual CEP data. The future study can simulate the supply chain recovery strategy and cost-saving performance. This study shows the importance of practising a circular economy to improve firm performance, attract more firms to be more involved in green practices, and help resolve disruption issues within supply chain networks. It is time for manufacturing firms to engage in CEP practices to improve the environment, reduce greenhouse gas emissions and maintain public safety and health. Also, when this practice began to be practised in the Malaysian manufacturing industry, the company created more job opportunities for those with the knowledge and skills to manage the CEP system and directly produce better quality staff.

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