Effect of Supply Chain Drivers on Leagile Implementation: Examining the Moderating Role of Industrial Cluster in Mazandaran province

By

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Abstract

Companies within industrial clusters must implement appropriate supply chain strategies to gain a competitive advantage in a market with unexpected fluctuations and demand uncertainty. This thesis demonstrated that implementing a leagile strategy significantly improves supply chain performance.

This study evaluates the effect of the five Supply Chain (SC) drivers consisting of production, location, inventory, transportation, and information, on implementing the leagile strategy through the Decoupling Point Position (DPP) approach. Also, the DPP's effect on the supply chain's performance has been studied by evaluating the Total Supply Chain Value (TSCV), which consists of cost, quality, service, and lead-time measures. Moreover, moderating effects of industrial clusters (i.e., Basis and Foundation, Business and Enterprise, and Market factors) between supply chain drivers and DPP were also examined.

The extant literature has been reviewed to propose a model highlighting the relationship between supply chain drivers, DPP, and TSCV, along with moderating variables.

The data used in this research were collected by surveying 212 participants within three industrial clusters, including furniture, agricultural machinery and equipment, and trout fish in Iran. Partial Least Squares and bootstrapping methods were used in SmartPLS-V3 software to conduct Confirmatory Factor Analysis and Structural Equation Modelling (SEM). Also, Slope Analysis has been shown to validate the findings of the Bootstrapping method.

The results demonstrated that the supply chain drivers of information sharing, production, inventory, and location significantly affect the leagile implementation in companies within industrial clusters. Also, the companies with a higher level of DPP show higher performance in their supply chain. In addition, Business and Enterprise, Market, Basis, and Foundation have a significant adverse effect on the relationship between supply chain drivers. DPP results demonstrated that companies within industrial clusters must establish, expand, and strengthen their relationships with the value chain members to boost their SC drivers' capabilities.

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LIST OF ABBREVIATIONS

AVE	Average Variance Extracted
Bas	Basis & Foundation
Bus	Business & Enterprise
CB/SEM	Covariance-Based SEM
CFA	Confirmatory Factor Analysis
CR	Composite Reliability
DP	Decoupling Point
DPP	Decoupling Point Position
DV	Dependent Variable
EF	Efficiency & Flexibility
ICT	Information and Communications Technology
Inf	Information
Inv	Inventor
IT	Information Technology
IV	Independent Variable
JIT	Just In Time
K-S	Kolmogorov-Smirnov
leagile	Lean And Agile Strategies
LLCI	Lower Limit Confidence Interval
Loc	Location
LSCS	Leagile Supply Chain Strategy
LSCV	Leagile Supply Chain Value
LVs	Latent Variable scores
Mark	Market
MCDM	Multi-Criteria Decision-Making
PLS	Partial Least Squares

PLS/SEM Variance-Based SEM

Pro	Production
R & D	Research and Development
SC	Supply Chain
SCM	Supply Chain Management
SEM	Semi Structural Modelling
SF	Sourcing Flexibility
SF	Sourcing Flexibility
SMEs	Small Medium Enterprises
SSA	Simple Slope Analysis
STDEV	Standard Deviation
TQM	Total Quality Management
Tran	Transportation
TSCV	Total Supply Chain Value
ULCI	Upper Limit Confidence Interval
VF	Vendor Flexibility

Chapter 1 Thesis Introduction

1.1 Introduction

Companies are constantly seeking process optimisation within their Supply Chain (SC) to improve their SC to respond to customers' demands effectively and reach a competitive advantage. The business failures in integrating optimisation strategies in SC would affect the viability and performance of SCs in the market (Nakandala and Lau 2019). The integration of optimisation strategies for integrating SC functions, processes, and structure between companies in SC are vital as the competition is not among the individual companies but their supply chain (Christopher et al. 2001; Christopher 2016). Because the moment customers receive an unsatisfactory service level, sluggish delivery leadtime, and low-quality product at a high price, they would switch and probably do not return in the future (Patel et al. 2020). Consequently, understanding the marketplace's demand and constraints and the companies' concerns within the SC is critical for developing and implementing SC strategies (Mason-Jones et al. 2000b).

Many companies pursue lean and agile SC strategies to reduce costs and improve customer demand to reach a competitive advantage (Qamar et al. 2018b). The lean concept is about doing more with less and is primarily concerned with eliminating waste or "Muda" to maximise profit. Shah and Ward (2003) defined lean manufacturing as a set of strategies such as Just-InTime (JIT) and Total Quality Management (TQM), working together synergistically to create a high-quality streamlined system. Conversely, the agile concept is about flexibility and rapid response to demand variation in a changing market environment, whether in product variety, volume, or mix (Christopher et al. 2001). Although both concepts are inherently different, they can be combined to form a total operational SC known as "leagile" (Naylor et al. 1999b).

Leagile strategy is a hybrid of conventional lean and agile strategies to help companies take advantage of both strategies in terms of efficiency and flexibility in an SC (Bhamra et al. 2020a). However, implementing the leagile strategy in SC is one of the main challenges of SC integration optimisation. Fadaki et al. (2020) argued a significant deviation exists between the companies' actual practices and the literature's conceptual theory of leagile strategy. According to (Bhamra et al. 2020a), this gap has remained in the literature, and scholars should develop appropriate methods for implementing leagile strategies within SCs.

The concept of "industrial cluster" or "industrial district" has been increasingly used and recognised as an essential part of regional development strategies and thinking in the past few

years (Claver-Cortés et al. 2020). Industrial clusters are regions of affiliated companies with similar functions or associated industries (Porter 2000).

The clusters intensify companies' competitiveness and promote innovation in a distinct region. The main advantages of industrial clusters are knowledge and technology sharing, efficient transportation systems, access to infrastructures and skilful workers (Lublinski 2003; Speldekamp et al. 2020). In addition, the success of industrial clusters is attributed to key characteristics such as geographic proximity and close social relations, which result in reduced transaction costs and nurtures trust. In addition, the formation of industrial clusters facilitates the flow of information, knowledge sharing, and access to a pool of skilled workers (De Marchi and Grandinetti 2014). Although lean, agile, and leagile SCs strategies have been studied in the SC literature, to the best of my knowledge, limited attention has been paid to analysing the effect of industrial clusters on the relationship between SC drivers and leagile implementation and SC performance.

Yusuf et al. (2014) evaluated the impact of the industrial clusters on the agility, competitive priorities, and performance of companies within oil and gas industrial clusters, and they couldn't find any strong relationship between competitiveness and industrial clusters in the oil and gas sector (Yusuf et al. 2014). This study examines the effect of SC drivers on implementing leagile strategy for companies within industrial clusters. To this end, three sectors that applied a leagile strategy based on the decoupling point position (DPP) method were selected to examine the leagile approach. So, the results could cover the literature gap by answering three questions, including:

1. What are the effects of SC drivers on DPP?
2. What are the moderating effects of the industrial cluster on the relationship between SC drivers and DPP?
3. How does DPP influence supply chain performance?

This research answered these questions by surveying companies within three industrial clusters: furniture, agricultural machinery and equipment, and trout fish. To this end, different measures have been identified to quantitatively evaluate the relationship between SC drivers, DPP, and SC performance. 212 SC experts from three industrial clusters were involved in the study. Smart PLS software used partial Least Squares and bootstrapping methods to conduct

confirmatory factor analysis and Semi Structural Modelling (SEM). Also, a Simple Slope Analysis has been shown to validate the moderating effect of the industrial clusters.

1.2 Motivation for this research study

Most companies attempt to consolidate their position in the market by formulating the best possible form of response to their customer demands, especially when the clients' demands are unpredictable. Companies must overcome the abovementioned challenges using various paradigms and strategies such as agility, leanness, and leagility. A lean approach eliminates non-value-added activities throughout the organisation and its supply chain. In contrast, the agile strategy emphasises satisfying the market change quickly by altering the organisational behaviour.

The leagile concept in manufacturing and the supply chain creates several advantages and benefits, including enhancing consumer relationships, creating competitive advantages, enhancing the quality of services, increasing the selling rate, controlling the expenses, improving the use of resources, eliminating non-value adding activities across the firms (Matawale et al. 2016).

Over the last two decades, many professionals and researchers have been exploring and contributing to the empirical analysis and theoretical development of the leagile conceptual framework (Mason-Jones and Towill 1999; Hallgren and Olhager 2006; Huang and Li 2010; Rahimnia and Moghadasian 2010; Soni and Kodali 2012; Matawale et al. 2013; Duman et al. 2015; Matawale et al. 2016; Fadaki et al. 2020; Vaishnavi and Suresh 2020). Heaney (2011) indicated that SC complexities due to the global business environment caused several issues for many businesses, including increasing lead times, inventory growth, and more extended logistic time control; as a result, the cost of supply chain management has increased significantly. On the other hand, customers and clients constantly look for better product quality, faster lead time, and lower prices. Therefore, most companies are looking for a flexible strategy such as a leagile strategy to reduce the cost of final products and respond more rapidly to the demands and supply.

Vaishnavi and Suresh (2020) stated that the leagile strategy could be applied to different industries, including information technology (IT), software development, textile, manufacturing, home appliance, healthcare, and automobile. Hence, this study selected three different heterogeneous supply chain clusters (furniture, agricultural machinery & equipment,

and trout fish) involving companies from multiple sectors to analyse how SC drivers in leagile strategy impact DP position and total supply chain value.

The selected companies for this study are SC and industrial cluster members, and their clusters include sectors such as food products, wood and fibreboard, metal, textile, chemical, machinery and equipment, and retail. This study has analysed the application of leagile strategy to determine how the companies and their supply chain must react to customer demands and how they could minimise waste, cost, and invaluable activities.

Several practical ways exist to implement the leagile strategy in a Supply Chain. Christopher and Towill (2000) reviewed various pragmatic strategies using the separation of 'Base' and 'Surge' demands strategy, the Pareto curve approach, and postponement methodology (known as DPP).

The DPP is a segregation point that creates a balance point between complexity, cost, and competitive advantages. Hallgren and Olhager (2006) introduced several factors that can impact DP's position in a supply chain network, including production lead time, business location, market, demand variance, delivery lead time, etc. In the current volatile business environment, many researchers have suggested that the DPP approach is a suitable method for satisfying customer needs (Fadaki et al. 2019a; Fadaki et al. 2020; Agrawal and Vinodh 2021; Ahmed and Huma 2021; Babaeinesami et al. 2021; Rabbani et al. 2021; Srinivasan et al. 2021).

This study investigates the effect of other independent variables such as market, basis & foundation, and business & enterprise on the position of DP and the impact of these factors on TSCV. Hence, these variables and factors were defined as moderators between the SC drivers and DPP to analyse whether they positively or negatively impact the leagile strategy of the selected companies.

1.3 Main Research Gap and Contribution to the knowledge

Leagile Supply Chain Strategy (LSCS) is a derivative of lean and agile strategies, which contends that finding a decoupling point at the desired end of an SC increases the responsiveness of companies positioned on the downstream side of the markets and concurrently decreases the cost of the companies set in the upstream side of the SC (Naylor et al. 1999a). Mason-Jones et al. (2000a) introduced the decoupling point and Information and Communications Technology (ICT) as the main factors in implementing LSCS effectively; they believe that the SCs' managers could improve customer service levels and reduce the lead times and costs by finding a suitable decoupling point and integrating a holistic ICT system.

Agarwal et al. (2006) used the multi-criteria decision-making (MCDM) technique to evaluate the effectiveness of the LSCS factors on the performance of the SC in terms of lead-time, cost, quality, and service level. They highlighted four main elements: ICT, flexibility, process integration, and market sensitiveness. Their findings demonstrated that LSCS could improve SC's competitive advantages in markets with unstable demand (Agarwal et al. 2006). However, their study did not assess the relationship between the identified factors and the product category. For instance, the effect of the market sensitiveness factor could increase due to the nature of the fast-moving consumer products. In contrast, in the other product category (functional products), the impact of the sensitivity could be different.

In another study, Fadaki et al. (2019a) stated that quantitative testing has revealed that the SCs of many Australian companies do not match what was conceptually expected. Therefore, they studied 299 Australian companies in different industrial sectors, such as food, wood, metal, retail, and textile. Production and inventory were two SCs' drivers evaluated to explore the impact of the leagile strategy on SC performance. Meanwhile, they analysed the effect of the uncertainty, which encapsulated Demand Uncertainty (DU), Supply Uncertainty (SU) and Internal Uncertainty (IU) on the positioning of DP within SCs; the results indicated that higher performance is attainable by minimising the level of deviation from a balanced supply chain by integrating both aspects of leanness and agility (See appendix 4: A conceptual framework of leagility index (LI)). However, the effect of other drivers of SC on DP was introduced in future research directions (Fadaki et al. 2019a).

Naim and Gosling (2011) reviewed the relevant research after Naylor et al. (1999a) study. They studied leagile ideas and assessed LSCS by considering the concepts of leanness and agility. They concluded that there is a lack of adequate research to cover different aspects of LSCV and the appropriate implementation methods. Many empirical studies were conducted on the products such as apparel, lighting, and fast-moving consumer products, however, the researchers need to evaluate LSCS by researching sectors such as fashion, sportswear, premium brands, food, power cable manufacture, furniture, leather goods, and carpet (Naim and Gosling 2011). They presented the research gaps in three dimensions, including 1) fundamental extension by noting LSCS factors; 2) research method by considering empirical approaches; and 3) applications of the LSCS (e.g., healthcare, military, and construction).

This study focused on covering the gaps in the literature by evaluating the impact of the LSCS factors on drivers and further on the SC performance (to improve the competitive advantages of the SCs) by developing an empirical framework and collecting data from the experts in SC

and exploring the effectiveness of the LSCS application in the furniture, agricultural machinery and equipment, and trout fish SC clusters. According to my research, no research has focused on the abovementioned problems. Most scholars directly analysed the impact of the LSCS on SC performance (or competitive advantages) without considering different drivers in the SC (Rezaei et al. 2018). Therefore, this study evaluates the relationship between leagile strategy factors and SC drivers and then between an SC driver and SC's performance metrics (TSCV). Rahiminezhad Galankashi and Helmi (2016b) demonstrated the necessity of analysing the LSCS factors regarding SC's drivers such as ICT, inventory, and distribution. Furthermore, they considered cost, quality, service level, and lead-time as metrics to evaluate the performance of the SCs. Applying the proposed construct in real SCs and evaluating the proposed framework and construct were presented as the main streams for future research (Rahiminezhad Galankashi and Helmi 2016b).

Consequently, this study aims to develop the relevant literature in the following gaps:

1. Lack of research evaluating the relationship between LSCS factors and SCs' drivers and between SCs' drivers and SCs' performance metrics (three levels construct).
2. Less attention has been given to the LSCS effective implementation in the furniture, agricultural machinery and equipment, and trout fish SCs in Iran.
3. Lack of construct for implementing LSCS efficiently and improving the competitive advantages of SCs in an industrial cluster.
4. Lack of research conducted in Iran to evaluate the best practices to implement LSCS.

1.4 Scope of the research

The scope of the current study is limited to companies that are a member of three industrial clusters in the north of Iran, including furniture, agricultural machinery and equipment, and trout fish. Companies with different industrial backgrounds are members of these three industrial clusters: food products, wood and fibreboard, metal, textile, chemical, machinery and equipment, and retail.

1.5 Research questions

To maximise the efficiency of SCs, scholars have considered different factors at different decision levels, including strategic, tactical, and operational levels. In the SC literature, Cost, quality, lead time and service are four metrics to evaluate the total performance of the SC (Mason-Jones et al. 2000a). According to the nature of the companies (e.g., types of products or

services, business model, industrial sector, and technological level), the involved companies have developed different levels of leanness and agility along with their SC to enhance the profit of their SC. So, developing and implementing a leagile strategy is not a trivial task for the SCs managers within companies.

Finding a balance between efficiency and flexibility (as to the significant outcome of the lean and agile strategies) is the main challenge for implementing leagile strategy at the company and SC levels. Therefore, implementing a leagile strategy affects the supply chain performance. In this study, a new model of leagile SC has been proposed, and the relationship between elements of the model was analysed to answer the following core research questions:

- Would SC drivers cause the change of DPP level in leagile SC?
- Would DPP adoption improve companies' supply chain performance within industrial clusters?
- Is the relationship between SCs' drivers and DPP moderated by the factors of industrial clusters?

The research questions have been addressed by developing hypotheses in Chapter 3.

1.6 Aim and objectives

According to the introduced gaps in the literature, and the research questions, this study seeks to address the effect of the SC's drivers on the leagile implementation, leagile strategy on SCs' performance, and the moderating effect of the industrial clusters on the relationship between SCs' drivers and leagile implementation. This study aims to address the following for the companies within an industrial cluster:

- To analyse the effect of the SCs' drivers on the leagile implementation by the DPP method.

Among different methods of implementing the leagile strategy, DPP is a promising approach that various researchers and practitioners apply. This study analyses the effect of five major SC drivers: inventory, production, transportation, location, and information on the DPP for the companies within industrial clusters.

- To analyse the effect of implementing a leagile strategy by decoupling points on the performance of an SC.

This study aims to examine the effects of implementing a leagile strategy on the performance of the SC in terms of time, lead-time, cost, and quality. Four metrics have been extracted by reviewing the literature to evaluate the total supply chain value. The study assessed the leagile strategy's advantages for companies within the industrial cluster.

- To evaluate the moderating effect of the industrial cluster factors on the relationship between SCs' drivers and leagile implementation.

This study analyses the relationship between SCs' drivers and leagile strategy for the companies within industrial clusters. So, the industrial cluster factors have been determined from the relevant literature. Their effects have been considered an indirect effect in the proposed model. The indirect effect has been considered as moderating effect. This study aims to test the moderating effect of industrial cluster factors on the relationship between SCs' drivers and leagile strategy by the DPP methods.

1.7 Outline of thesis

At the end of this chapter, it is necessary to present the thesis outline and briefly explain how this study achieved its main aims and objectives. The thesis consists of seven chapters (including an introduction in chapter one) to reflect all aspects of the Effect of Supply Chain Drivers on Leagile Implementation: Examining the Moderating Role of Industrial Cluster in Mazandaran province.

Chapter 2: Literature Review

Chapter 2 reviews the preceding literature of this study, considering two main related topics of this thesis, including supply chain (SC) and industrial cluster. The first section of this chapter reviews the SC literature to explore the SC's strategies, drivers, and performance measures. The second section of this chapter investigates the literature on industrial clusters to identify the most critical factors and processes related to supply chain performance. Finally, the research gaps, fundamentals of the conceptual model, proposed hypotheses, and the main contributions of this study will be addressed at the end of this chapter.

Chapter 3: Research Methodology

Chapter 3 reviews the research methodologies to determine the best method to conduct this study and achieve the aims and objectives of the thesis. This chapter will discuss the research onion method, including the philosophical approach to theory development, methodological choice, strategy, and time horizon to select the best techniques for this research

project. Regarding the nature of this study, the research participants, and considering the COVID-19 situation, the questionnaire survey will be explained as the primary approach to collect the data for this study. This chapter covers collection procedures, statistical methods, data analysis techniques, and applied quality criteria. Furthermore, the concepts of interaction effects and simple slope analysis will be reviewed in this chapter. At the end of this chapter, the deductive method flow chart presents all this thesis's main steps.

Chapter 4: Basic Data Analyses and Descriptive Tests

Chapter 4 covers the fundamental data analysis and initial statistical tests to evaluate whether the collected data showed enough reliability and validity to proceed with the data in the next chapter. This chapter covers the demographic analysis of the collected data, normality tests (including the Kolmogorov-Smirnov test and Shapiro-Wilk test), and descriptive analysis of the data for each driver and variable. Moreover, this chapter reviews the reliability statistics, including Cronbach's alpha for all drivers and moderators, and covers the total item correlation of data. The reliability of data if the items or measures were deleted from the construct (Cronbach's Alpha if Item deleted) will be reviewed in this chapter. For all analyses of this chapter, the SPSS software (IBM SPSS Statistics V.26) will be applied. At the end of this chapter, the flow chart presents all the main steps of quality criteria analyses, normality tests, and descriptive tests and shows how the data feed-forward to the next chapter.

Chapter 5: Confirmatory Factor Analysis (CFA) and Structural Equation Modelling (SEM)

This chapter presents the primary analyses of this thesis, including confirmatory factor analysis (CFA) and structural equation modelling (SEM) using SmartPLS (V3).

This chapter examines the proposed construct, including 67 measures in 10 variables, five factors, three moderators, DPP and TSCV. This chapter covers the quality criteria of the construct and variables after each round of analysis, including AVE, CR, and Cronbach's alpha. Also, it includes three primary analyses: CFA of drivers, CFA of moderators, path analysis of main hypotheses (H1, H2, H3, and H5), and their sub-hypotheses. The flow chart demonstrates all conducted investigations and considered quality criteria within CFA and SEM at the end of this chapter.

Chapters 6 and 7: Implications, Discussion, and Conclusion

The last two chapters summarise the study's main Implications, Discussion, and Conclusions and emphasise the thesis's primary contribution. Chapter 6 covers the effect of information sharing, production, location, and inventory on DPP. It also reviews the managerial implication of this study. In chapter 7, the answers to the research questions, theoretical contributions, and empirical contributions will be covered. This chapter will also consider the current study's limitations and recommendations for future research.

Chapter 2 Literature Review

2.1 Introduction

This chapter divides the literature into two main related areas: supply chain (SC) and industrial cluster. The first section reviews the SC literature to explore the SC's strategies, drivers, and performance measures. The industrial cluster literature is reviewed in section two to identify the most critical factors and strategies related to supply chain performance. Finally, the research gaps and the main contributions of this study have been addressed, which are the fundamentals of the conceptual model and proposed hypotheses.

2.2 Supply Chain Drivers

SCs' managers emphasised the importance of collaboration among companies within the SC, from the supplier to the market. Chopra and Meindl (2007) defined Supply Chain Management (SCM) as:

"The systemic, strategic coordination of the traditional business functions within a particular company and across businesses within the supply chain, for the purposes of improving the long-term performance of the individual companies and the supply chain as a whole."

Based on the SCM definition, it involves integration and coordination between production, distribution, and inventory management (Agus and Shukri Hajinoor 2012). Chen et al. (2019) defined SCM as a system that encapsulates a set of drivers, including suppliers, producers, distributors, and customers, linked together via information sharing to implement the SC strategies effectively. Min (2015) defined inventory management, commodities distribution, production, and information as the four main drivers of the SC. Hugos (2018) categorised all operations of the SC into four main categories: planning, sourcing, making, and delivering. Figure 2-1 shows the production, inventory, location, transportation, and information as five major supply chain drivers to provide a final product.

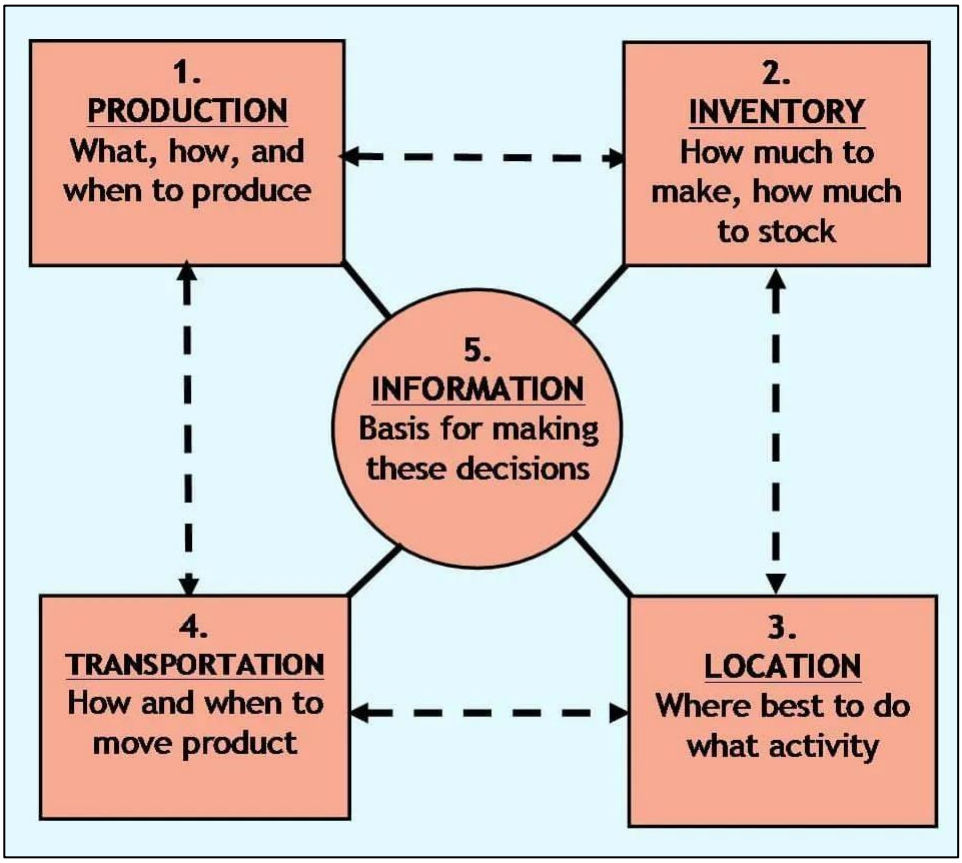


Figure 2-1-The five major supply chain drivers (Hugos, 2018).

To compete in the marketplace, companies within SC must make an informed decision for each driver. For example, suppose a supply chain strategy serves a high volume of a good(s) in a market. In that case, all the companies within the SC should aim to reduce the cost of production, inventory, transportation, and operational cost of SC, including information sharing and location. In the following sections, the drivers of the SC are reviewed based on the definition of (Min 2015; Hugos 2018).

2.2.1 Production

According to (Fisher 1997), there is a strong relationship between the type of SC and the type of product; thus, the structure of SCs must match with the product's type; otherwise, SCs would be exposed to the risk of mismatch between product's type and SC's type (See appendix 1: Functional versus innovative products: differences in demand). He categorised the products into "functional" and "innovative" groups. Functional products are standardised products with stable demand and a long-life cycle. On the other hand, innovative products, known as fashion, have unstable demand and a short life cycle. Furthermore, the production processes of

functional and innovative products are different. So, this study aims to evaluate the effect of the leagile strategy on SC performance in terms of production driver.

SCs require customising and improving the quality of their products while reducing costs and shortening lead-time due to the clients' requirements and market demands (Hartley 2017). Therefore, companies within SC are subjected to significant pressure to increase the efficiency and effectiveness of their production capabilities to remain in the competition (Carvalho et al. 2017). From a manufacturing perspective, effectiveness has been defined as the ability to respond to customer demand, and efficiency has been described as measuring how an organisation's resources are utilised economically enough to reflect customer satisfaction (Li et al. 2018). Table 2-1summarised the measures of production.

Table 2-1-Measures of the production driver.

Measures	Reference
Production variation cost	(Heo and Chung 2014; Duffie et al. 2017)
Product cycle time	(Chiu et al. 2016; Ben-Ammar et al. 2020)
Due date	(Duffie et al. 2017; Kim et al. 2020)
Demand	(Mason-D'Croz et al. 2019; Zambrano-Asanza et al.2019)
The utilisation rate of Production	(Leung and Chan 2009; Li et al. 2016)
Product value (performance to cost)	(Fang et al. 2008; Whalen 2019)
Waste ratio	(Dıaz et al. 2003; Xiao et al. 2019)

2.2.2 Distribution and transportation

Distribution and transportation of the material among companies in an SC play a critical role in the success of the SC (Hugos 2018). Transportation facilitates the flow of products throughout the SC, whether in the form of a component or final product. The distribution system determines the retrieval and transportation of products from the supplier to the final customer (Wangsa and Wee 2019). The distribution system has gone through an upheaval since the advent of the internet. In contemporary SCs, some companies tend to cut the intermediaries and sell directly to the end customer (Kozlenkova et al. 2015). This way, they can reduce the cost of purchasing for the end client, acquire direct feedback from final customers, and capture the latest trend (Ross 2015). For example, the orders will be shipped to the customers once the customisation process is completed. Depending on the companies ' strategy, the final products could be shipped either to the distribution centre and then to retailers, directly to retailers, or from the distribution centre to end customers.

Furthermore, three different postponement approaches were defined in the literature (Pagh and Cooper 1998). Indeed, the SC managers can control the distribution of the material in the SC by holding the material (even the final product) at different positions within the SC. For example, three types of postponement approaches were introduced in the literature, including procurement, manufacturing, and delivering postponements. Bagchi and Gaur (2018) demonstrated the importance of the postponement approaches for managing distribution in SC by analysing the trade-off between methods and associated costs. While in the procurement approach, the manufacturer can postpone the orders of raw materials until the actual orders are received from the downstream side. In the manufacturing approach, the SC's manager postpones production to customise the products according to the market's demand. In delivering approach, the final products would be held in strategic stock at a central location until the orders are transmitted from the market. Due to the importance of the distribution driver and its impact on the supply chain strategies and, further, on the SC performance, this study aims to analyse the effect of the distribution driver on the implementation of leagile strategy. Consequently, finding the best position for the DP in terms of distribution is a challenge in implementing the Leagile strategy. Table 2-2 summarised the measures of distribution driver.

Table 2-2-Measures of the distribution driver.

Measures	Reference
Distribution effectiveness	(Abrahamsson and Brege 2004; Park* 2005)
Direct/indirect distribution	(Seifert et al. 2006; Pishvaee and Rabbani 2011)
Distribution efficiency	(Amiri 2006; Pop et al. 2015)

2.2.3 Inventory

SCs' inventories consist of components and finished products held within SC (Hosseinifard and Abbasi 2018). Companies stock products in their inventory as a buffer against uncertainty, providing companies with the capability to become flexible and respond more rapidly to changes within the market (Ma et al. 2018). Cannella et al. (2018) stated that keeping inventory can be expensive. They focused on a single echelon of the SC, including retailers who satisfy the customers' clients by ordering the products directly from the manufacturers. They adopted a nonlinear analytical expression to perform different experiments by considering six independent variables. They demonstrated that SC managers

could control the cost of the SCs because the inventory level within SC is a significant cost element in most businesses (Cannella et al. 2018).

In a leagile SC, the critical stocking point is held at the DP to balance responsiveness and costs associated with inventory. The manufacturer at downstream delays the customisation/assembly for as long as possible at the inventory level until the exact attributes/scale of the product's requirement is identified. As soon as demand is realised and accepted, the customisation/assembly phase will initiate. Indeed, companies can work under different practices (DP positions) to hold their final product and raw materials (input from upstream companies). To evaluate the performance, Naylor et al. (1999a) analysed five inventory control approaches: Buy-to-Order, Make-to-Order, Make-to-Order, Make-to-Stock, and Ship-to-Stock (See appendix 2: Supply chain structure and decoupling point). Indeed, optimising decisions regarding the inventory driver of SC affects implementing SC strategies and further enhances the SC performance (Cannella et al. 2018). Table 2-3 summarised the measures of the inventory driver to analyse its impact on SC strategy.

Table 2-3-Measures of the inventory driver.

Measures	Reference
The volume of raw materials	(Windisch et al. 2015; Shepherd et al. 2017; Voronkova et al. 2020)
The volume of final products	(Noya et al. 2016; Owen et al. 2018)
Constant demand	(Raa and Aghezzaf 2008; Kaur and Kumar 2018)
Fixed order point	(Babaï et al. 2009; Kostić 2009)
Inventory holding cost	(Torkul et al. 2016; Khatua et al. 2017; Yadav and Swami 2019)
Inventory turnover	(Hu et al. 2010; Sato et al. 2014)

2.2.4 Information

Information sharing acts as a facilitator agent to elevate transparency regarding markets and suppliers' sides and the interaction among companies in an SC. For example, the information sharing system aids the upstream side of an SC by receiving data concerning the amount of procurement required on the downstream side of the SC, which results in a higher forecast precision. On the other side, receiving order data and markets' needs help the companies in SC to capture the latest trend in a timely and accurate manner.

ICT as a tool of information sharing in SC is a system that facilitates coordination among SC companies, which enables synchronisation between production scheduling, distribution planning, and inventory control (Zhang et al. 2016). Wu and Cheng (2008) indicated that increasing the rate of sharing information between the partners decreases the cost of inventory,

production, location, and distribution. According to (2000), SC members coordinate their processes through the feed-forwards/backward information-sharing mechanism. One of the dynamics of SC optimisation is enabled by information sharing to make better decisions regarding production planning, assigning capacity, order processing, and material planning (Vahdani and Ahmadzadeh 2019). Mensah et al. (2015) state that the lack of adequate information sharing in SC could lead to chaotic behaviour, panic, uncertainty, and an increase in preventable costs. Zhang and Yang (2016) analysed how information sharing aids SCs' managing to improve supply performance. They explored the effects of information sharing and found that ICT positively affects supply performance if the uncertainty is high.

The extent of information sharing varies and depends on the nature of business within SC regarding outsourcing and the level of trust amongst the partners, as members always risk sharing sensitive information such as manufacturing scale, production schedule or inventory level (Ojha et al. 2019). Nevertheless, contemporary SCM practices encourage building cooperative and meaningful long-term relationships among partners of the SC and urging companies to share their risks reasonably (Nishat Faisal et al. 2006). Due to the impact of information sharing driver on SC performance, this study considers information sharing as one of the SC drivers for evaluating its impact on the implementation of SC strategy. Table 2-4 summarised the measures of the information sharing driver.

Table 2-4-Measures of the information driver.	
Measure	Reference
Accuracy of information	(Ge and Helfert 2013; Ishii and Ohba 2018)
Level of uncertainty	(Datta and Christopher 2011; Chen et al. 2017)
IT/ICT development	(Zhang et al. 2016; Mandić and Praničević 2019)
External force	(Wong et al. 2011)
Table 2-4- Measures of the information driver.	
Measure	Reference
Top management support	(Hanna et al. 2010; Jitpaiboon and Sharma 2013)
Value of companies (within SC)	(Brandenburg and Seuring 2011; Brandenburg 2013)
Trust among companies (within SC)	(Sharfman et al. 2009; Tejpal et al. 2013)
Companies' commitment (within SC)	(Wan Ahmad et al. 2016; Sriyakul et al. 2019)

2.2.5 Location

Location decision plays a critical role in the effectiveness and efficiency of the SCs. SCM connects location decision problems and strategic and tactical decisions (Doolun et al. 2018). Indeed, deciding facilities' location and determining material flow within the SC network affect other SCs' drivers, such as inventory and transportation (Melo et al. 2009). Ambrosino and Grazia Scutellà (2005) argued that location, inventory, and transportation decisions are fundamental drivers in logistic management and play an essential role in advancing SC performance. Rather than just finding an appropriate location for the facility, the location addresses the SC's activities assigned to the locations. The SC managers should allocate the location of operations (e.g., production, holding, distributing locations) within SC.

Many scholars (Tlahig et al. 2013; Lara and Grossmann 2016; Emelogu et al. 2019) studied the effect of location policy, including the centralisation of the distribution system and its relation to the performance of SCs. Their finding demonstrated that centralising the facility's location within SC increases the performance of the SCs from an economic viewpoint. In contrast, the decentralised policy in allocating activities would improve the service level and responsiveness of SCs. Various measures have to be considered, including the fixed and variable costs regarding the whole activities within SCs (e.g. production and transportation) (Ishfaq and Sox 2011; Tirkolaee et al. 2020), infrastructures and services (Farahani et al. 2019), and access to skilled labour (Zarrinpoor et al. 2017) to decide on the facility location. So, the location decision affects the performance of SCs. After determining the location of facilities within the SC, the material and information flow from supplier to the customer should be considered. Also, the location decision represents the basic strategy for designing SCs (Ahmadi Javid and Azad 2010). In this manner, this study aims to analyse the effect of location driver on implementing the leagile strategy. Table 2-5 summarised the measures of the information.

Table 2-5-Measures of the location driver.

Measure	Reference
Fix and variable cost of company within SC (e.g., land, energy)	(Saif and Elhedhli 2016; Swayamsiddha and Singh 2017)
Access to appropriate infrastructure (e.g., IT, and transport)	(Hajibabai and Ouyang 2013)
Access to services (e.g., financial, and legal services)	(Field and Meile 2008; Giannakis et al. 2018)

Availability and quality of labour (education and skill)	(Karimi et al. 2017; Nye 2018)
Environmental stability (e.g., government and tax policies)	(Gonzalez et al. 2013; Gajbiye and Laghate 2017)

2.3 Supply chain strategies

Uncertainty in the marketplace, fast development of technologies, and globalisation affect companies within SCs (Wieland et al. 2020). Nowadays, companies within an SC compete with companies within other SCs. Indeed, the overall performance of all companies in an SC indicates their achievement or failure (Korpeoglu et al. 2020). Companies must serve their products and services according to markets' requirements. To this end, SC managers must choose and implement the most suitable strategies for all the companies within their SC (Lemieux et al. 2015). So, SC managers regularly look for strategies to improve their competitive advantages. Implementing an effective strategy can assist them in satisfying customers' demands and advancing their performance against competitors (Gligor et al. 2015).

The SC strategy significantly impacts companies' performance at an organisational level. Indeed, SC strategy acts as a bridge among companies within an SC. Therefore, all companies within an SC must make their strategy compatible with the overall SC strategy to improve their efficiency and the overall performance of their SC (Qi et al. 2011). Qi et al. (2017) presented the relationship between SC strategies and companies' strategies. They emphasised that scholars should pay more attention to analysing the effects of SCs strategies and companies' strategies.

Various SC positions, market demographics, rules and regulations of the countries, nature of the products, and emerging new markets are the main motives for developing the relevant literature (Qi et al. 2017). This study aims to evaluate the effect of SC drivers on the implementation of leagile strategy and the overall performance of SC. Also, industrial clusters' features have been considered as moderator factors that impact the implementation of leagile strategy. To this end, the following sections will review SC's lean, agile, and hybrid leagile strategies.

2.3.1 Lean

Lean and agile are two SC strategies that managers may choose to adjust SC's drivers; lean strategy denotes a company's capability to reduce production and distribution costs (Chopra and Meindl 2007). Also, it is focused on efficient processes and cost optimisation related to SC drivers such as production, information, and financial flows (Rai et al. 2006).

Iyer et al. (2019) proved that high operating scale capacities are configured into lean capabilities.

Defining the value is the first step to developing a lean SC. The companies should find the activities and operations that add value to their products based on the market viewpoint (Khorasani et al. 2020). The added value of the operations depends on the end-user's perception and how much they are eager to pay for it. Chen et al. (2019) defined waste as the whole thing that does not add value. Scholars argued that lean is an effective strategy in stable and predictable markets with a low change and high volume (Christopher et al. 2006).

Emerging new markets worldwide and their significant force in reducing the final prices led to the adoption of the lean approach by SCs (Boyle et al. 2011). So, companies developed a cost-oriented strategy to produce their products at the lowest possible costs (Arnas et al. 2013). The pressure to reduce product costs, respond to customer needs, competition between companies and market pressure are the main drivers for deploying lean strategy by companies within SCs (Orji and Liu 2020). So the SC managers expect to deliver products of high quality at a lower price (Behrouzi et al. 2011).

2.3.2 Agile

The capability to rapidly reconfigure process features is another competitive factor of companies in SCs. The agile strategy relies on flexibility and adaptability in a dynamic, rapid, and continual response to the market's shifts in a competitive atmosphere (Denning 2018). Nishat Faisal et al. (2006) found that the agile strategy reduces inventory level, helps SC encounter market variability, improves responsiveness to market demand, and increases the SC's companies' collaboration. Scholars like Dubey and Gunasekaran (2015); Tse et al. (2016) emphasised that responsiveness is one of the main factors in increasing competitive advantages, which could be reached by implementing an agile strategy. This noted that SC managers could identify fluctuations in the market demand more accurately through the agile process. Furthermore, Pearson et al. (2010) argued that the agile strategy is appropriate for SCs that offer small volumes, high margins, a short life cycle and innovative products. Indeed, the time dimension is the most critical feature of the agile strategy. In agile SC, the SC and its members (companies within SC) should rapidly adapt their network and processes according to end-user requirements (Srinivasan et al. 2020).

While cost reduction is the main driver behind the lean strategy, the instability and changing market is the leading force in deploying agile strategy (Tarafdar and Qrunfleh 2017). Currently, fluctuation in the market is happening at a much faster frequency than ever before.

Growing uncertainty and changes (based on the numbers and characteristics) in the marketplace are not easily predictable (Tseng and Lin, 2011). Many scholars believe that agile strategy is a dynamic capability (Irfan et al. 2019). This market-oriented strategy addresses trade-offs among companies, customers, and new technologies. Skilful personnel, creativity, and knowledge play critical roles in implementing effective agile SC (Bhamra et al. 2020a). The main drivers for developing agile SC include a) necessity for responsiveness, efficiency, and effectiveness of operations and network, rapid changes in customers' needs, increased request for customised products/services, and intense competition for satisfying consumers. Table 2-6 summarises agile strategy's drivers and outcomes (Stefanelli et al. 2019).

2.3.3 Leagile

Some scholars believe that deploying only lean or agile strategies could not improve the competitive advantages of the SCs, e.g. (Ciccullo et al. 2018b; Qamar et al. 2018a). The lean strategy focuses on cost while the agile strategy maximises responsiveness. To deploy the advantages of both lean and agile strategies simultaneously, Naylor et al. (1999a) introduced the leagile system to increase the capability of SCs in unstable markets and further improve the competitive advantages of SCs. Applying leagile helps the SC managers have the benefits of lean and agile strategies in terms of cost, quality, services, flexibility, efficiency, and responsiveness (Ciccullo et al. 2018a). As a result, a leagile strategy for SCs is recommended as a suitable SC strategy. Because SCs' managers realise that if markets receive a disappointing service level, improper delivery lead-time, low-quality product, and high prices, they would leave and never return to their SCs (Aslam et al. 2018).

Market force and customers' requirements are the main concerns pushing companies towards deploying a leagile strategy. Leagile helps companies within an SC to respond to predictable and unexpected changes. Harrison et al. (2019) emphasised that when companies encounter unstable demand and a wide variety of customer needs, a rapid response would be a higher priority than removing waste. However, the SC should implement a leagile strategy according to their features (e.g., product type and market instability level). Stefanelli et al. (2019) reviewed the leagile literature. They extracted the main drivers of the leagile SC, including competitive market force, unpredictable environment, responsiveness importance, market-oriented, and the force to reduce the cost. Table 2-6 summarises the drivers and outcomes of agile strategy.

Table 2-6-Drivers and expected effects and outcome of lean, agile, leagile strategies (Stefanelli et al. 2019)			
	SC strategies		
	Lean	Leagile	Agile
Drivers	• Pressure to reduce product costs • Respond to customer needs • Competition between companies • Market pressure	• Force of a competitive marketplace • Unpredictable environment • Responsiveness • Focus on service level • Product price and costs	• Necessity for responsiveness • Unstable markets • Effectiveness of operations and network • Rapid changes in customers' needs • Increase the request for customised products • Intensive competition for satisfying consumers
Expected effects and outcomes	• Waste decrease • Cost decrease • Higher quality • Just-in-time supply • Efficiency improvement • Saving-Time	• Cost-effectiveness • Dynamic capability • Efficiency	• Responsiveness • Fast reactions • Customised products • customer effectiveness

Leagile SC enables companies to deploy the lean strategy on the upstream and agile on an SC's downstream side. In leagile SC, upstream companies aim to manufacture components of final products as generic as possible. Then, the products are customised according to the customers' requirements (Chan et al. 2009). There are different advantages to each strategy. Table 2-7 compares the main features of lean, agile, and leagile supply chains. The agile strategy aims to increase the capability of SCs in dealing with the unstable and unpredictable marketplace on the downstream side of SC; the lean strategy removes the non-value-adding operations of SCs from the upstream side. Mason-Jones et al. (2000b) deployed market qualifiers and market winners to identify the difference between lean and agile in cost, quality, lead-time, and service level. Since the quality and lead-time are the essential criteria for the performance of SCs, both strategies pay equal attention to their development. However, there are different perceptions in terms of service level and cost. As noted before, in agile SC, the main objective is providing a high service level to customers' orders, and in lean SCs, the main goal is cost reduction (MasonJones et al. 2000b). Agarwal et al. (2006) extracted the main attributes of the lean,

agile, and leagile SC according to (Naylor et al. 1999a; Mason-Jones et al. 2000a; Olhager 2003; Bruce et al. 2004). Also, the main characteristics of each strategy have been recognised in terms of the defined attributes. Agarwal et al. (2006) identified the attributes of lean, agile, and leagile SC.

Table 2-7-Comparison of lean, agile, and leagile supply chains (Fisher 1997; Agarwal et al., 2006).

Features	Lean	Leagile	Agile
Demand	Predictable	Volatile and unpredictable	Volatile
Product variety	Low	Medium	High
Product life cycle	Long	Short	Short
Customer drivers	Cost	Service level	Lead-time and availability
Profit margin	Low	Moderate	High
Dominant costs	Physical costs	Both	Marketability costs
Stock out penalties	Long term contractual	No place for stock out	Immediate and volatile
Purchasing policy	Buy goods	Vendor managed inventory	Assign capacity
Information enrichment	Highly desirable	Essential	Obligatory
Forecast mechanism	Algorithmic	Both/either	Consultative
Typical products	Commodities	Product as per customer demand	Fashion goods
Lead time compression	Essential	Desirable	Essential
Eliminate Muda	Essential	Arbitrary	Desirable
Rapid reconfiguration	Desirable	Essential	Essential
Robustness	Arbitrary	Desirable	Essential
Quality	Market qualifier	Market qualifier	Market qualifier
Cost	Market winner	Market winner	Market qualifier
Lead-time	Market qualifier	Market qualifier	Market qualifier
Service level	Market qualifier	Market winner	Market winner

2.4 Leagile implementation: Decoupling point method

Christopher and Towill (2000) provided three methods for integrating lean and agile strategies and taking advantage of leagile SC, including Decoupling point (DP), Pareto curve, and 'base' and 'surge' demands methods (See Appendix 3: Hybrid strategies).

As shown in Figure 2-2, The Pareto curve (80:20 rule) method categorises products into two main categories: the first category is 20% of the products accountable for 80% of total revenue. This line of products is known as fast-moving goods with relatively stable and predictable demand. Therefore, lean philosophy (Make-to-stock) should be implemented to facilitate cost-efficiency and efficient replenishment. Meanwhile, the remaining line of products, which accounts for 80% of total output, should follow agile thinking. These products are known as slow-movers with attributes such as high fluctuations in demand pattern and short life cycle, prompting the producers to generate supply only when the orders are received (make-to-order).

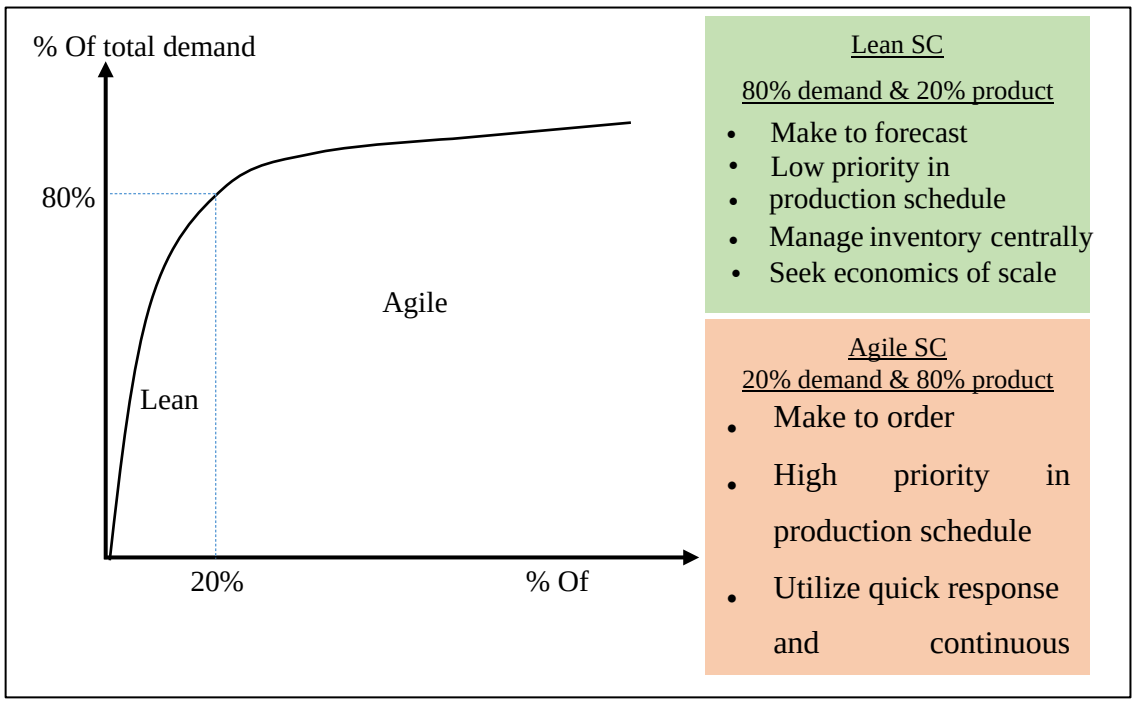


Figure 2-2-Pareto curve method (Christopher and Towill, 2001).

Gattorna (1996) used the demand pattern to develop a practical leagile SC method, called 'base' and 'surge' demands. Figure 2-3 highlights this difference with one possible level scheduling solution where capacity demands are smoothed by intelligent switching of 'base' production.

In leagile SC, the base demand is produced with a lean strategy to decrease the cost. In contrast, surge demand responds with more flexibility and is generally associated with more cost and higher profit margins than Base demand; This SC strategy is increasingly being used in the fashion industry through outsourcing the labour-intensive activities in developing nations to meet the 'base' demand and producing for the 'surge' demand in the local market to fulfil the orders as quickly as possible.

Base demand can be estimated by historical data, while surge demand is unstable due to the dynamic characteristics of marketplaces. So, in leagile SC, the Base demand is produced with a lean strategy to decrease the cost. In contrast, surge demand responds with more flexibility and is generally associated with higher cost of production. Furthermore, the companies located in low-cost areas (cheap labour and energy) could supply Base demand.

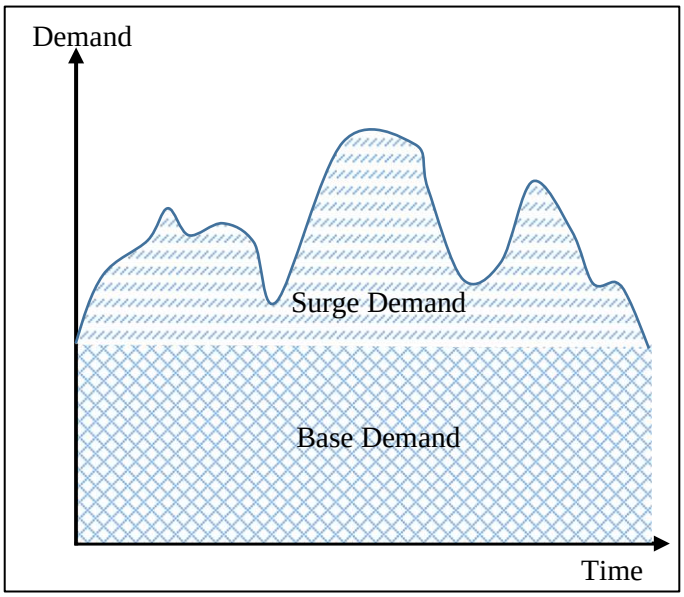


Figure 2-3-Base and surge demands method (Christopher and Towill, 2001).

The Decoupling Point (DP) method deploys the lean strategy up to an appropriate point so that the SC's remaining segment can adopt an agile strategy (Shahin et al. 2016; Fadaki et al. 2019a). At this point, the activities appertaining to forecast-driven scenarios at the upstream and those associated with order-driven scenarios intersect (Bhamra et al. 2020b). The DP primarily was proposed for material and inventory flow over SC (Christopher and Towill 2000). Mason-Jones and Towill (1999) defined the information DP for controlling demand information flow from the marketplace to the supplier side within SC. Figure 2-4 shows the Decoupling point position in leagile supply chain.

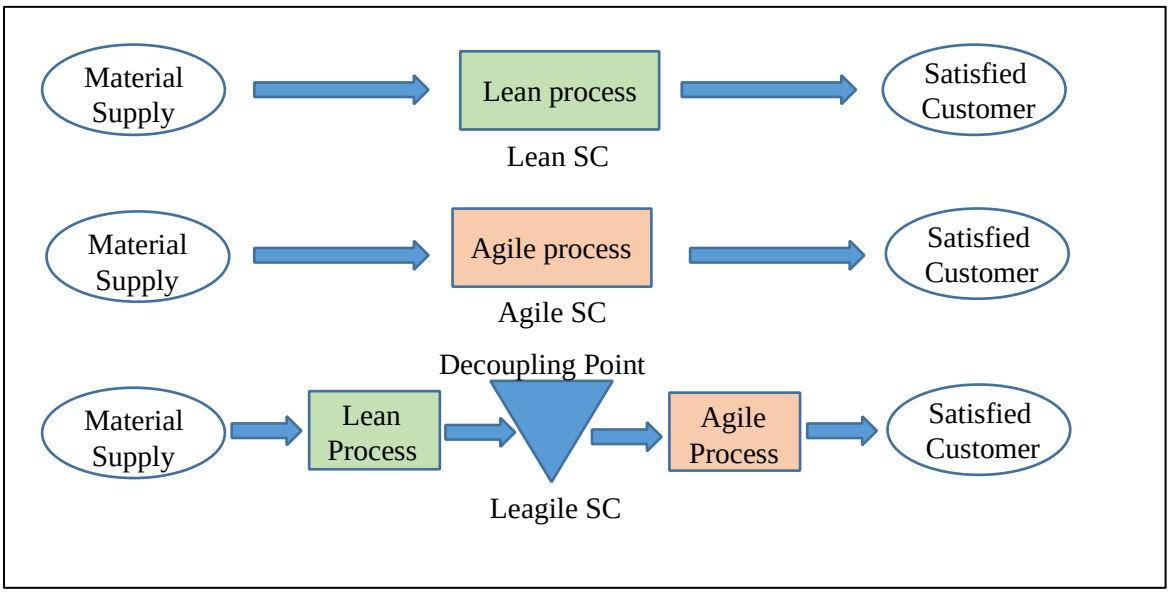


Figure 2-4-Decoupling point position in leagile SC (Naylor et al., 1999).

The key idea behind the DP positioning is to produce functional products, modules, or components as efficiently as possible at the upstream and hold strategic inventory as a buffer at the DP while leaving the rest of the assembly, production, or customisation processes to the downstream side to figure out the actual requirement of the customers (Mason-Jones and Towill 1999; Naylor et al. 1999a). Mason-Jones and Towill (1999) argued that to maximise the performance of a leagile SC, the traditional material DP should be distinguished from information DP. The standard SC model places the information DP at the same point as the material DP, effectively positioning the information DP as close as possible to the end consumers. Mason-Jones and Towill (1999) claimed that this strategy is ineffective, resulting in upstream information distortion. Therefore, the information DP should be positioned as far as possible downstream. So, the entities at the upstream can make decisions based on undistorted information and increase forecast accuracy.

Furthermore, the position of DP can be changed based on pinpointing a proper balance between productivity and flexibility (Rudberg and Wikner 2004). The function of DP is determined by prioritising cost and service level (Figure 2-5) and the market condition. When there is minor variation in demand and the marketplace is stable, cost becomes the main priority (winner); thus, the DP is pushed downwards towards the market; if demand fluctuation is high and requires a high product mix, then the service level becomes a top priority (winner),

and DP is pushed upwards towards the suppliers. Indeed, the position of the DP could change the SC strategy from a pure lean approach to a pure agile strategy upon various SCs' drivers (Fadaki et al. 2020).

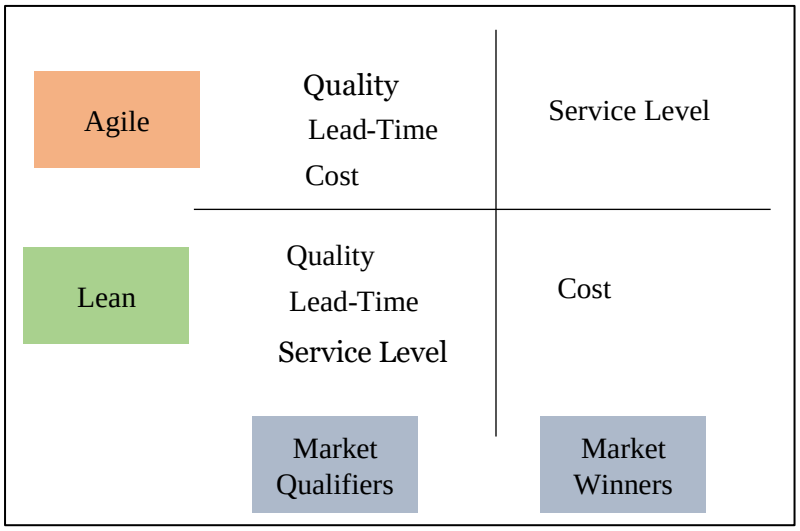


Figure 2-5-Market winners and market qualifiers for agile versus lean supply (Mason-Jones et al., 2000b).

Literature in leagile supply chain strategy proved that the SCs manager must develop leagile due to the nature of the SCs in terms of production, inventory, information, distribution, and location drivers. This study aims to measure the leagile with the measure that has been reported in Table 2-8.

Table 2-8-Measures of the leagile using DPP.

Measure	Reference
Pressure to respond to all market needs	(Stefanelli et al. 2019; Agarwal et al., 2006; Bhamra et al., 2020a; Chan et al., 2009).
Pressure to maximise the efficiency and reduce product costs	(Stefanelli et al. 2019; Agarwal et al., 2006; MasonJones et al. 2000b; Soni and Kodali, 2012; Bhamra et al., 2020a).
Predictable demand with a low level of the final product	(Stefanelli et al. 2019; Agarwal et al., 2006; Agrawal and Vinodh, 2021; Bhamra et al., 2020a; Duman et al., 2015; Galankashi and Helmi, 2016; Kumar et al., 2019).
Volatile demand with a high level of the final product	(Stefanelli et al. 2019; Agarwal et al., 2006; Galankashi and Helmi, 2016; Agrawal and Vinodh, 2021; Bhamra et al., 2020a; Kumar et al., 2019).
Information enrichment is obligatory in SC	(Stefanelli et al. 2019; Agarwal et al., 2006; Amir, 2011; Babaeinesami, et al., 2021; Duman et al., 2015; li et al., 2020).

Information enrichment is desirable in SC	(Stefanelli et al. 2019; Agarwal et al., 2006; Amir, F., 2011; Babaeinesami, et al., 2021; li et al., 2020)
Distributing products according to the markets demand	(Wangsa and Wee 2019; Bagchi and Gaur 2018; Kozlenkova et al. 2015; Ross 2015; Pagh and Cooper 1998).
Distributing products to the market after receiving the actual demand from the market	(Wangsa and Wee 2019; Bagchi and Gaur 2018; Kozlenkova et al. 2015; Ross 2015; Pagh and Cooper 1998)

2.5 Supply Chain Performance

According to (Gunasekaran et al. 2004), many SCs have not maximised the potential of their chain's capabilities due to failure to adapt suitable metrics to evaluate their SC's performance. There is extensive literature on SCs dealing with SC's performance metrics and competitive advantages. Indeed, scholars have aimed to identify the optimal SC performance metrics according to the nature of SC's product types and other SC features. For instance, Arif-Uz-Zaman and Nazmul Ahsan (2014) presented SC metrics of time, cost, quality, and flexibility for evaluating high volume, low-price products under the lean strategy.

Shepherd et al. (2017) addressed the shortage of studies on the performance metrics of SCs by reviewing the literature and suggesting possible areas for future research. They argued that scholars should pay more attention to the SCs' performance metrics and measurement systems and must evaluate the effectiveness of the metrics for different types of SCs.

Naylor et al. (1999a) identified four performance metrics, including lead-time, service, cost, and quality, to evaluate the performance of an SC (Figure 2-6). To implement a leagile strategy in SC by DP method, upstream companies adopt a lean strategy where the main focus is on principles of cost-efficiency (Martínez-Jurado and Moyano-Fuentes 2014). Therefore, according to Hill's matrix (Hill 1992), the cost would be a winner, whereas the lead-time, quality, and customer service would be qualifiers. On the other hand, the downstream side relates to demand instability and is mainly focused on responsiveness (agility), so the market winner in customer service and market qualifiers are quality, cost, and lead-time (Mason-Jones et al. 2000b). Maestrini et al. (2017) reviewed the SC performance metrics literature and presented the necessity of evaluating the performance of the SC by considering different drivers of the SCs. They categorised SC performance metrics as quality, service, time, and cost. Also, they emphasised that less attention has been paid to evaluating SCs through

empirical study (Maestrini et al. 2017). This study attempts to assess the effect of the leagile strategy on the SCs' performance based on the four metrics, including quality, service, lead-time, and cost (Mason-Jones et al. 2000a).

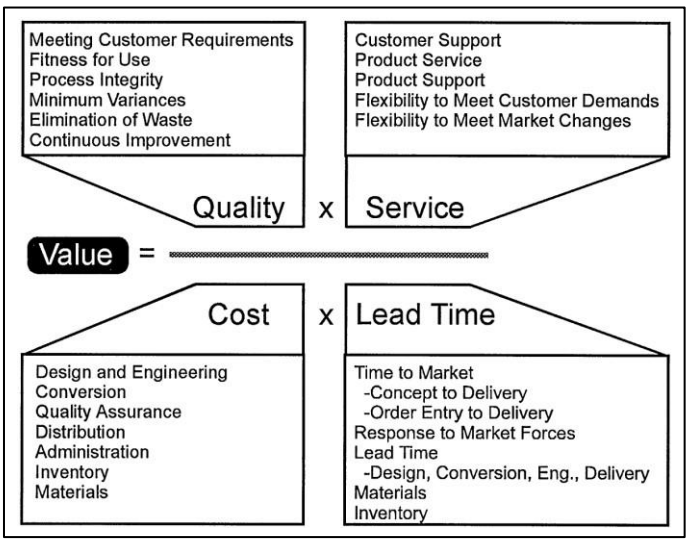


Figure 2-6-Total Supply Chain Value Metric (Mason-Jones et al., 2000a).

2.6 Selecting Unit of Analysis

Selecting a unit of analysis is a critical step in the research design, as it helps ensure that the study is well-designed and capable of producing meaningful results (Rashid et al., 2019). By considering factors such as the research question, research objectives, the field of study, the level of analysis, the significance of the study, and the potential limitations. So, in this study, the researcher used inventory, transportation, production, location and information are used as SC drivers to determine the effect of the Decoupling Point Position (DPP) on the TSCV.

TSCV is measured by four elements (Cost, Quality, Lead-Time, and Service Level). All the measures were standardised and vary between 0 to 1.

There are several other ways to evaluate supply chain performance. For example, a few common metrics used in supply chain management are:

- Inventory turnover: The number of times inventory is sold and replaced over a given period. This metric measures a company's ability to manage its inventory effectively (Tripathi and Talukder, 2020).
- Order fulfilment rate: The percentage of customer orders that are delivered on time and completed. This metric measures the efficiency of the company's order fulfilment process (Khan et al., 2020).

- Lead time: The time it takes from when an order is placed to when it is delivered to the customer. This metric measures the speed and efficiency of the supply chain (Chang and Lin, 2019).
- Supplier performance: An evaluation of the performance of a company's suppliers, including measures such as on-time delivery, quality, and responsiveness to issues (Meena et al., 2022).
- Cost of goods sold (COGS): The cost of the goods sold during a given period, including direct materials, direct labour, and manufacturing overhead. This metric measures the efficiency of the company's manufacturing process (Rahiminezhad Galankashi and Mokhatab Rafiei, 2022).
- Return on investment (ROI): The return generated by an investment, expressed as a percentage of the investment's cost. This metric measures the overall effectiveness of a company's supply chain investments (Kamble and Gunasekaran, 2020).

These are just a few examples of the metrics that can also be used to evaluate Total Supply Chain Value (TSCV). The specific metrics used will depend on a company's goals and priorities, as well as the nature of its business, the company's operating model and the products it sells (Rahiminezhad Galankashi and Mokhatab Rafiei, 2022). Total Supply Chain Value (TSCV) refers to the overall value created by a company's entire supply chain network, including suppliers, manufacturers, distributors, and retailers (Yang, 2022). The aim is to optimise the SC performance to maximise TSCV created by each participant in the supply value chain and ensure that all players work together effectively to achieve the common goal of delivering value to customers (Zhang and Gao, 2020). Furthermore, the TSCV approach considers the full range of costs and benefits associated with a supply chain, including transportation costs, inventory holding costs, supplier risks, and the value of product features and services. By considering these factors holistically, companies can decide how to optimise their supply chain to maximise overall value and improve customer satisfaction. Therefore, TSCV is a comprehensive measure that considers the full range of costs and benefits associated with a supply chain, making it a critical concept to evaluate supply chain performance for several reasons as suggested below (Seyedhosseini et al., 2011, Lu, 2011, Khoei and Ghosh, 2021):

- Holistic view: TSCV considers all aspects of the supply chain, including suppliers, manufacturers, distributors, and retailers. This allows companies to make data-driven

decisions about optimising their supply chain and ensure that all players work together effectively to deliver value to customers.

- Customer focus: TSCV puts the customer at the centre of the evaluation, ensuring that the supply chain is optimised to deliver the best customer experience. This helps companies to build strong relationships with customers and establish a competitive advantage in the marketplace.
- Data-driven decision-making: TSCV is based on data and analytics, which allows companies to make decisions based on real-world results and performance metrics. This enables companies to identify areas for improvement and make informed decisions about optimising their supply chain for maximum value.
- Integration: TSCV helps to integrate the different functions and participants in the supply chain, promoting collaboration and coordination. This helps to reduce waste, improve efficiency, and increase overall value.
- Flexibility: TSCV can be tailored to meet the specific needs of each company and can be used to evaluate the performance of specific supply chain segments or individual participants. This allows companies to focus on the most critical areas and adopt a suitable approach that accommodates their needs and priorities over time.

Similarly, three different clusters (with different products, processes, networks, and resources) were analysed in this study which was also standardised.

2.7 Industrial Cluster

The concept of “industrial cluster” or “industrial district” has been increasingly used and recognised as an essential part of regional development strategies and thinking in the past few years (Claver-Cortés et al. 2020). Industrial clusters are regions of interconnected companies with similar functions (Porter 2000). The clusters intensify companies' competitiveness and innovative potential in a distinct region. The main advantages of industrial clusters are knowledge and technology sharing, efficient transportation systems and infrastructures, and access to skilled workers (Lublinski 2003). Italian small- and medium-sized companies in an industrial cluster that successfully competed in global industries popularised the classical concept of industrial districts introduced by Alfred Marshall (Gereffi and Lee 2016). Industrial clusters' success was credited with several key characteristics, such as geographic proximity and close social relations, which helped reduce transaction costs and nurture trust, and informal

networks, facilitating the flow of information, knowledge, and skills (De Marchi and Grandinetti 2014).

2.7.1 Industrial Cluster Strategies

Industrial clusters build a more efficient network through mutual interaction of companies and forming a coupling interface. The structure of industrial clusters shows the synthesis of the SC, value chain, and knowledge chain. This means that the essence of industrial clusters is the knowledge flow, geographic proximity, innovation sharing, and collaborating companies (Cao 2008).

Das (1998) presented the complex role of industrial clusters for developing SMEs in developing countries. He analysed multiple features of the companies within industrial clusters, including production, strategies, internal processes, cooperative action, and labour circumstances. His findings demonstrated that to develop industrial cluster strategies, attention should be paid to building trust, company networks, product quality, and employment.

Belso-Martínez (2008) studied four industrial footwear clusters in Spain to develop effective strategies. His research shows that industrial cluster strategies should build strong relationships and interactions among companies within the cluster. In addition, strategies should consider the company's outsourcing activities with other companies outside the industrial cluster. Cao (2008) used game theory to choose the industrial cluster innovation strategies and determined that stable equilibrium and joint innovation strategies are optimal for vertical and horizontal knowledge integration of SCs.

Mazzanti and Zoboli (2009) provided evidence by testing a set of hypotheses regarding networking activities, Research and Develop (R&D), quality of relations among companies within the industrial cluster, structural companies' features, environmental policy pressure, and companies' performances within an industrial cluster in Northern Italy. They revealed that the firm's structural characteristics matter less than induced policy costs, R&D, and innovative oriented industrial relations. R&D applications seem to be associated with networking activities substituting for size-related economies of scale. They argued that endogenous factors driven by company strategy and distinctive local features are more important than exogenous factors of companies and structural relationships within industrial clusters. Kurniawan et al. (2013) examined the strategies of industrial clusters in Malaysia. The traditional cake and catfish industries were the focus of their study. They believe that the strategy of industrial clusters should support leading companies aiming to advance their profit margins. Because with the growth of major companies within the industrial cluster, other small companies can

also grow. Their results showed that a comprehensive strategy is needed to grow industrial clusters, considering the market, finance, capital, knowledge, and entrepreneurship (Kurniawan et al. 2013).

Agile companies improved operational efficiency, resilience, reliability, and responsiveness can help them manage their resources and minimise their environmental impact. Also, the role of clusters as a strategy for economic exploitation of oil and gas resources is explored by (Yusuf et al. 2014), who empirically examined the results of deploying an agile strategy among companies within the oil and gas industrial cluster. Their findings demonstrated that membership in the industrial cluster enables higher agile practices regarding competitiveness and performance.

Pisa et al. (2015) illustrated the impacts of forming industrial clusters as a strategy to improve competitiveness and economic diversification in the Northwest Province of Africa. They demonstrated that forming industrial clusters would improve the economic activity of the considered region. Structural change in the economy of the specified area through the formation of industrial clusters was observed with a crucial finding that industrial clusters are notable contributors to structural changes in the economic landscape with the promotion of cluster specific exports.

Da Silva Andrade et al. (2016) presented a strategic management model for the companies within industrial clusters that comply with competitiveness standards expected by the market. To the best of my knowledge, no research in the literature examined the relationship between leagile strategies and the performance of companies within industrial clusters. Undoubtedly, implementing agile, lean, and hybrid leagile strategies needs to be studied due to the complex communication among companies within the industrial cluster. In addition, the role of industrial clusters in regional economic development in developing countries increases the importance of the studies.

2.7.2 Industrial clusters factors

Determining the success factors of industrial clusters is essential for analysing their performance and capabilities. The success of the industrial cluster could be analysed through effectiveness criteria such as goal attainment or the satisfaction level of companies (Mandell and Keast 2008). An effectiveness analysis provides insights into the ability of industrial clusters to reach goals at company and cluster levels (Turrini et al. 2010). An industrial cluster achieves its goals when its companies develop technological innovation to improve services and product quality (KENIS and PROVAN 2009). Porter (2000) made a breakthrough for the cluster concept, advocating specialisation based on historical strength by highlighting the

power of industrial clusters. Porter emphasised that several external factors could contribute to a company's performance. His ‘‘diamond model” includes interrelated forces to explore industrial clusters. These forces include input conditions, local demand conditions, supporting industries, and competition (Sun et al. 2009).

The effectiveness of industrial clusters is the same as the efficiency of companies and inter organisational relations, which are affected by several factors arising from industrial clusters' background, structure, and functioning processes (Turrini et al. 2010). The context of an industrial cluster can be described as the environment within which the cluster was formed. External or planning constancy is a requirement that assures the system's stability. Planning constancy is presented in the contract of political and regulatory statuses and financial resource consideration (David and Han 2004). The financial resources of clusters generally originate from government funding and companies’ investment (Klerkx and Leeuwis 2009).

Trust is another essential factor in cooperation among companies in an industrial cluster context. Indeed, trust is necessary for generating competitive advantages for the companies in an industry cluster (Mesquita 2007). Responsibility, fairness, and trustworthiness in the cooperation among companies in the industrial cluster help negotiation manners and cooperation activities (i.e., information sharing) (Luo 2008).

The local area is frequently stated as a contextual requirement for forming clusters. Colocation of companies initiates a process of localised specialisation of industrial activities based on the significant number of specialised, skilful employees, the provision of a greater variety of industry-specific elements, economic element of talent acquisition, and more efficient conveyance of information among co-located companies (Audretsch and Feldman 1996; Baptista and Swann 1998). These dynamics enable companies to create a local milieu foundation that may promote knowledge spill-overs and stimulate learning, innovation, and adaptation (Malmberg et al. 2002). According to (Porter 2000), clustering is enabled through mechanisms that support the interchange and flow of information among geographically proximate companies, forming a foundation that funds innovative activities and competitiveness.

The fundamental properties of an industrial cluster are usually set by the industrial cluster's stakeholders and facilitators. The cluster structures define processes within the cluster and regulate the relationships among companies and the cluster facilitators. The cluster structures form the cooperation among the companies within the cluster, determining their relationship strength and affecting their overall performance (Eisingerich et al. 2010). An essential

structural component in a cluster is the level of formalisation. Precise and rigid rules control internal cluster relationships and formalised decision-making processes allowing cluster facilitators to make informed decisions according to their objective rules (Jansen et al. 2006). Also, formalisation promotes implementing and codifying the best-fitted methods (Zander and Kogut 1995).

The function of industrial clusters consists of different features and aspects to define the strategic behaviour and operation of cluster facilitators, who are intermediaries between firms and companies. Howells (2006) illustrates that intermediaries are essential for providing consultancy and information or technology brokerage. The crucial requirements for the intermediaries or cluster facilitators are knowledge and information about applied technology, existing networks, and related professional experience in the cluster (Kirkels and Duysters 2010). Also, a crucial part of cluster facilitators has detailed tasks and goals. Csikszentmihalyi (1975) stated that complex tasks and goals are requirements to navigate the cluster's workflow. Therefore, the tasks and goals in an industrial cluster must be perceivable, reachable, and complementary to enabling the cluster facilitators to carry out their roles and formulate and implement a cluster strategy (Provan et al. 2008). Usually, advanced transformational management can help cluster facilitators to enhance their corporation and involvement among the firms and companies in the cluster. The transformational leader focuses on arranging resources inside the group and cluster, motivating the group members, and creating commitments for the organisation by communicating its vision and considering the goals (Podsakoff and Organ 1986). A more distinguished level of commitment lessens the threat of opportunistic action, reduces the transactional costs, and improves the cluster's effectiveness (Hong et al. 2009).

The operational and strategic behaviour of the industrial clusters is also restricted by the need for customising their management plan. Industrial clusters must choose a cluster-specific management plan to satisfy their companies. They should accumulate cluster-specific human capital and manage the cluster based on its specific features, like the position of companies in the value chain (Poppo and Zenger 1998). Investments in a customised management strategy can positively affect the effectiveness of clusters, as companies are willing to pay for services and goods provided by the clusters (Jungwirth et al. 2011).

Local networks are market information sources, helping companies join international markets. Co-location and local communications create new market opportunities because companies are co-located or work together in a network. Managers must extend networking

aptitudes to maximise network opportunities (Brown et al. 2010). Local specialised markets and industrial clusters have been a driving power in developing markets, from rural to economic base markets. Strong links between the growth of industrial clusters and specialised markets based on social and economic companies have driven the maturity of market relations. The role of specialised markets is vital as a dominant channel for distributing products in a country and abroad (Bellandi and Lombardi 2012).

While most research on industrial clusters has examined the effect of individual factors on the success of industrial clusters, few researchers have focused on comprehensively identifying the factors affecting the success of industrial clusters. In addition, most of the research was based on case studies to find the best practices in managing industrial clusters. In contrast, less attention was paid to identifying the success factors of industrial clusters using quantitative methods. Kaabinezhad et al. (2014) reviewed the literature to extract the factors affecting the success of industrial clusters. They used a Network Analytic Process (NAP) approach to analyse the effect of factors and their interrelationship in the context of industrial clusters. Their findings show that the human resources and the environment of companies, sales policies, and cooperation level within industrial clusters are the most influential factors in the success of industrial clusters. Also, they labelled factors in three dimensions: basis and foundation, business and enterprise, and market. Del Giudice et al. (2014) surveyed 943 technological companies in four countries to analyse the relationship between industrial cluster involvement, organisational learning, and organisational adaption. Their findings show that inter-company collaboration and communication, social network, financial strategy improvement, and product quality enhancement are the most critical factors in increasing the performance of industrial clusters. This study reviewed the literature of industrial clusters to find the critical factors and measures on the success of industrial clusters and reported in Table 2-9.

Table 2-9-A summary of key literature - Industrial clusters factors and measures.		
Industrial cluster factor	Measure	Reference
Basis and foundation	Skilful employees	(ZHU et al. 2005; Lee et al. 2012; Figueiredo et al. 2014).
	Working capital (financial resources)	(Zhong et al. 2006; Lei 2009; Veselovsky et al. 2015; Andreeva and Shevchik 2017)
	Technology	(Iammarino and McCann 2006; Coletti and Policy 2010; Libaers and Meyer 2011)
	Innovation and R&D	(Eraydin et al. 2005; Hamaguchi and Kameyama 2007; Nishimura and Okamuro 2011; Turkina and Van Assche 2018)
	Internal communication (within the industrial cluster)	(Bathelt et al. 2008; Verčič et al. 2012; Men 2014)
	Controlling the external environment of the industrial cluster	(Adeoye et al. 2012; Mai and Phuong 2016)
	Controlling the internal environment of the industrial cluster	(Hornsby et al. 2002; Länsiluoto et al. 2016)
	Effective policy	(Frattini et al. 2013)
	Work specialisation	(Karlsen and Development 2005; Chikán et al. 2008; Petrenko et al. 2019)
	Rules and regulations	(Gereffi and Lee 2016; Lund-Thomsen et al. 2016)
Business and enterprise	Strong suppliers	(Steinle et al. 2008; Szanyi et al. 2010)
	Strong cooperation	(Newlands 2003; Brenner 2005; Oprime et al. 2011)
	Reliable companies	(Padalkar et al. 2019)
	Honest companies	(De Vries and Duque 2018; Lee et al. 2018)
	Cooperation level	(Felzensztein and Gimmon 2008; Oprime et al. 2011)

	Strong competitors	(Newlands 2003; Venkataramanaiah et al. 2007; Daddi et al. 2012)
	Rules and regulations	(Gereffi and Lee 2016; Lund-Thomsen et al. 2016)
	Goal alignment	(Pieper et al. 2008; Lepmets et al. 2012)
Market	Sale policies	(Moreland-Russell et al. 2013)
	Local market demand	(RAHJI and Adewumi 2008; Gao and Rai 2019)
	Foreign market demand	(Robertson and Wood 2001; Rong et al. 2015)
	Local market outlook	(Torbaghan et al. 2016)
	Global market outlook	(Mussatto et al. 2010; Kilian and Murphy 2014)
	Connection degree of the local value chain	(Hainzer et al. 2019)
	Distance to foreign markets	(Ojala 2015; Antunes et al. 2019)
	Obstacles and limitations of foreign markets	(Śliwiński and Śliwińska 2014)

2.8 Conceptual Framework

A conceptual framework represents concepts, constructs, and variables of research. This study proposed a conceptual model by reviewing the relevant studies in the literature.

2.8.1 Hypothesis Development

The relationship analysis of the DPP index, supply chain drivers and the total supply chain value has been conducted by developing research hypotheses. The research hypotheses are extended for responding to the following research questions:

- What are the key drivers of a leagile supply chain in the industrial clusters?
- What are the key factors of the industrial cluster for implementing a leagile supply chain effectively?
- How does Decoupling Point Position influence supply chain drivers?

As a result of the literature review, the drivers of the SCs and key metrics of supply chain performance were recognised. Figure 2-7 shows the supply chain drivers, DPP, and total supply chain value constructs. This study attempted to find the appropriate practice for implementing leagile strategy in the industrial clusters. So, the impact of the SCs' drivers on the DPP index (H_1) and supply chain performance (H_2) and other forces of the industrial cluster factors are considered (H_3, H_4, H_5).

2.8.1.1 Supply chain drivers & Decoupling Point Position

H_1: Supply chain drivers cause the change in the positioning of the Decoupling Point in the leagile supply chain.

The constructs of supply chain drivers consisting of the production, location, inventory, transportation, and information are analysed through the following hypotheses in detail:

- H_{1-1}: The production driver causes the change in the positioning of the Decoupling Point in the leagile supply chain.
- H_{1-2}: The location driver causes the change in the positioning of the Decoupling Point in the leagile supply chain.
- H_{1-3}: The inventory driver causes the change in the positioning of the Decoupling Point in the leagile supply chain.
- H_{1-4}: The transportation driver causes the change in the positioning of the Decoupling Point in the leagile supply chain.
- H_{1-5}: The information driver causes the change in the positioning of the Decoupling Point in the leagile supply chain.

2.8.1.2 Decoupling Point Position & supply chain performance

SCs' managers could increase their performance by managing their drivers. Scholars believe that drivers significantly impact the competitive advantages of SCs (Wangsa and Wee 2019). SC's managers must find a position where both efficiency and responsiveness in SC's drivers are high to improve companies' output and TSCV (Kozlenkova et al. 2015). Hence, the effect of the DPP on the supply chain performance is tested through the hypothesis H_2.

H_2: DPP adoption leads to better supply chain performance of the companies within industrial clusters.

2.8.1.3 Moderating variable: Basis & Foundation

Figure 2-8 shows the effect of the basis and foundation variable as a moderator on DPP. The central hypothesis (H_3) and its sub-hypotheses (H_{3-1}, H_{3-2}, H_{3-3}, H_{3-4}, and H_{3-5}) are also shown clearly in Figure 2-8.

H_3: The relationship between supply chain drivers and DPP is moderated by the Basis & Foundation factor of the industrial clusters.

To understand the impact of moderating variables, the following hypotheses will be tested:

- H_{3-1}: The relationship between production driver and DPP is moderated by the Basis & Foundation factor of the industrial clusters.
- H_{3-2}: The relationship between location driver and DPP is moderated by the Basis & Foundation factor of the industrial clusters.
- H_{3-3}: The relationship between inventory driver and DPP is moderated by the Basis & Foundation factor of the industrial clusters.
- H_{3-4}: The relationship between transportation driver and DPP is moderated by the Basis & Foundation factor of the industrial clusters.
- H_{3-5}: The relationship between information driver and DPP is moderated by the Basis & Foundation factor of the industrial clusters.

2.8.1.4 Moderating variable: Market

Figure 2-9 shows the effect of the market variable as a moderator on DPP. The central moderator hypothesis (H_4) and its sub-hypotheses (H_{4-4}, H_{4-4}, H_{4-4}, H_{4-4}, and H_{4-5}) are also shown in Figure 2-9.

H_4: The relationship between supply chain drivers and DPP is moderated by the market factor of the industrial clusters.

- H_{4-1}: The relationship between production driver and DPP is moderated by the market factor of the industrial clusters.
- H_{4-2}: The relationship between location driver and DPP is moderated by the market factor of the industrial clusters.
- H_{4-3}: The relationship between inventory driver and DPP is moderated by the market factor of the industrial clusters.
- H_{4-4}: The relationship between transportation driver and DPP is moderated by the market factor of the industrial clusters.
- H_{4-5}: The relationship between information driver and DPP is moderated by the market factor of the industrial clusters.

2.8.1.5 Moderating variable: Business & Enterprise

Figure 2-10 shows the effect of the business and enterprise variable as a third moderator on DPP. The central moderator hypothesis (H_5) and its sub-hypotheses (H_{5-1}, H_{5-2}, H_{5-3}, H_{5-4}, and H_{5-5}) are also shown clearly in Figure 2-10.

H_5: The relationship between supply chain drivers and DPP is moderated by the Business & Enterprise factor of the industrial clusters.

- $H_{5\text{-}1}$: The relationship between production driver and DPP is moderated by the Business & Enterprise factor of the industrial clusters.
- $H_{5\text{-}2}$: The relationship between location driver and DPP is moderated by the Business & Enterprise factor of the industrial clusters.
- $H_{5\text{-}3}$: The relationship between inventory driver and DPP is moderated by the Business & Enterprise factor of the industrial clusters.
- $H_{5\text{-}4}$: The relationship between transportation driver and DPP is moderated by the Business & Enterprise factor of the industrial clusters.
- $H_{5\text{-}5}$: The relationship between information driver and DPP is moderated by the Business & Enterprise factor of the industrial clusters.

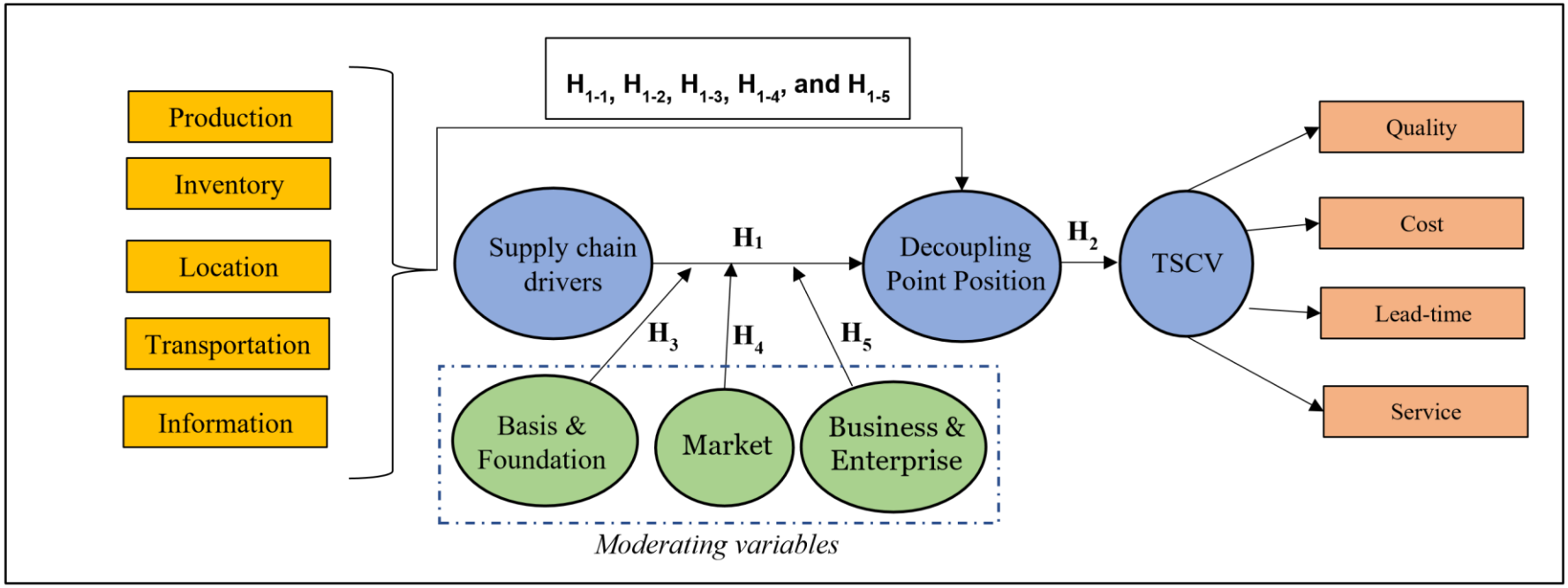


Figure 2-7-Main research model

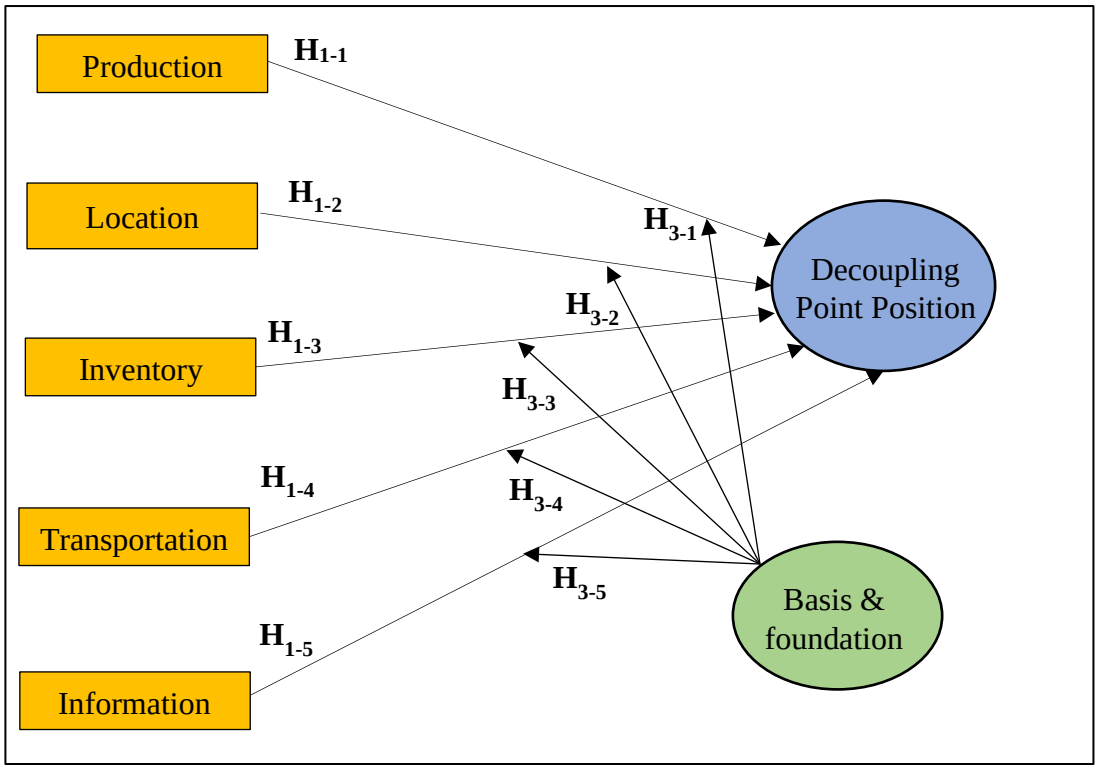


Figure 2-8-Complementary research model. Effect of Basis and Foundation as moderator on DPP.

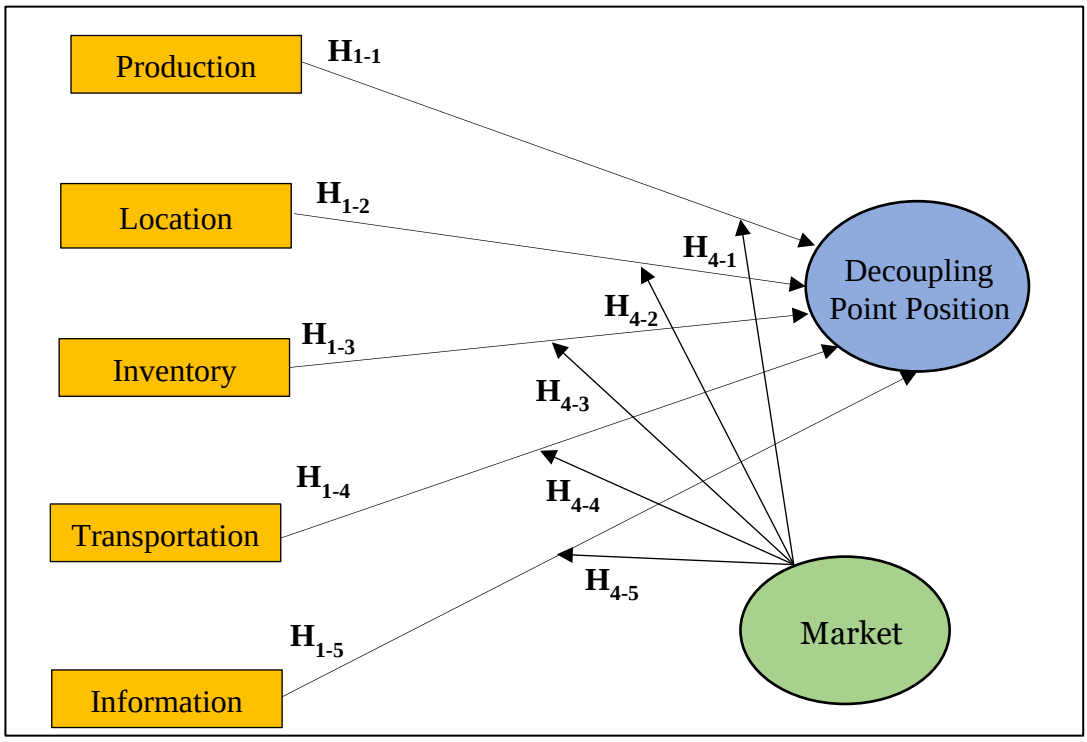


Figure 2-9-Complementary research model. Effect of Market as a moderator on DPP.

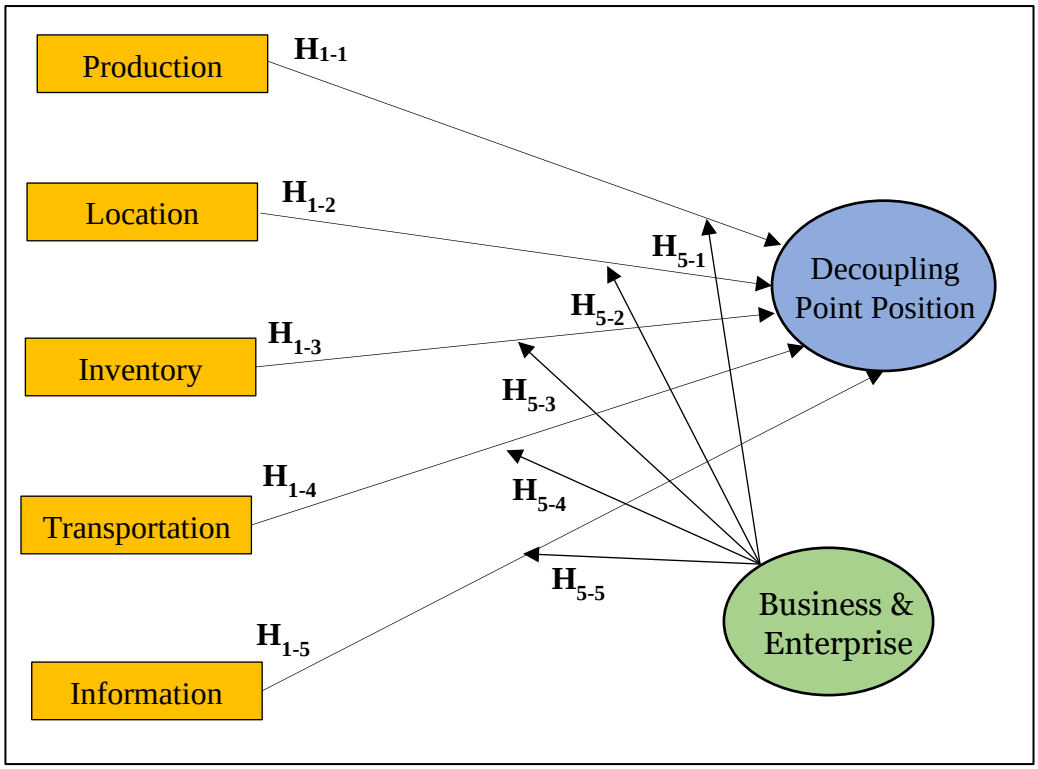


Figure 2-10-Complementary research model. Effect of business and enterprise as a moderator on DPP.

2.9 Research Gap and Summary of LR

The main novelty of this study is determining DP's role in the leagile supply chain using three homogeneous clusters. In addition, the moderation effect and its impact on DP were studied to determine how DP's position was changed by considering the moderators such as basis & foundation, market, and business & enterprise.

This study focused on covering the gaps in the literature by evaluating the interrelationship between SC drivers and the position of DP and further the impact of DP position on the SC performance (to improve the competitive advantages of the SCs); developing an empirical framework and collecting data from the experts in different SCs and exploring the effectiveness of the leagile strategy implementation in industrial clusters; examining the effect of industrial cluster factors as moderator variables on the position of DP in leagile SCs.

Some scholars emphasised the lean performance in the supply chain which is referred to as the cost-based approach to improve the performance of SC by eliminating or reducing all the extra activities from the design of the products to final delivery to the customer (Chen et al., 2020). On the other hand, the term agility is an approach to introducing new products into unpredictable, volatile, and turbulent markets to satisfy a variety of clients' demands in different sizes and volumes considering the high speed and high quality of the products (Rahimi and Alemtabriz, 2022). In addition, agility in the SC is an approach that responds to market changes as quickly as possible to meet customer needs. The companies in an industrial cluster that have adopted the agile strategy must have robust external and internal capabilities to communicate their needs with their key suppliers and effectively meet the customers' needs (Petermann and Zacher, 2020). Nevertheless, this study considered the leagile strategy for the selected unit research to determine the role of DP on the selected SCs.

Soni and Kodali (2012) emphasised that effective LSCS implementation could improve the competitive advantages of the SCs and companies within it. They considered cost and response time as two principal metrics for evaluating the level of competitiveness of the SCs. However, no standard construct exists to form the LSCS for any SCs. Indeed, SC managers must find the most appropriate construct for implementing LSCS depending on their SCs' attributes Hence, they surveyed the Indian manufacturing sector and collected data from experts inside India by developing a construct for implementing LSCS effectively.

In terms of the selected method, the most appropriate multi-criteria decision-making was selected to analyse the collected data and complete the aim and objective of this study. Most scholars selected a similar method to conduct their research study. For instance, Haq and Boddu

(2017) applied an MCDM technique to find the leagile strategy factors for improving the performance of companies operating in the perishable food sector in India. Their results demonstrated that virtual networking (collaborative relationship), ICT, strategic alliance within SC, and flexibility were the most influential factors for implementing LSCS. Li et al. (2019) explored the critical factors of LSCS in selecting suppliers in the Chinese textile industry. Their research presented quality, service level, customer satisfaction, and lead time as four essential metrics to eliminate the cost in the Chinese textile industry.

Moreover, most scholars directly analysed the impact of the leagile on the SC performance (or competitive advantages). At the same time, different drivers in the SC (Rezaei et al. 2018) play a critical role in the success of the SCs. Therefore, this study aims to find the suitable position of DP through SC based on each driver. Galankashi and Helmi (2016) showed the necessity of analysing the DP position concerning SC's drivers such as ICT, inventory, and distribution. Furthermore, they considered cost, quality, service level, and lead time as metrics to evaluate the performance of the SCs. Applying the proposed construct and framework in real SCs was highlighted as the mainstream for future research.

Consequently, this study aims to develop the relevant literature in the following gaps:

1. A lack of research has evaluated the position of DP in terms of SC drivers, including production, inventory, information sharing, distribution, and location.
2. Less attention has been paid to examining industrial clusters' main factors quantitatively.
3. Lack of research has focused on implementing leagile SC for industrial clusters effectively.
4. There is no research in the literature considering the moderating effect of industrial cluster factors on the position of the DP within leagile SC.

To complete the above research gaps, this study selected three companies that are a member of three industrial clusters in the north of Iran as the scope of research to investigate the effect of supply chain drivers on leagile strategies. The industrial nature of the three companies was limited to furniture, agricultural machinery & equipment, and trout fish.

Error! Reference source not found. summarised the most important methods and findings of the relevant studies reviewed in this chapter to identify the gap research of this study.

Table 2-10-Important research and their significant findings reviewed in this study	
Study	Findings
Naylor et al. (1999a)	Emphasising that agile strategy is a practical approach to dealing with fluctuating demand and unstable markets. Also, the lean strategy could be adapted to fix demand, and the companies can reduce their manufacturing costs. However, a leagile as hybrid strategy could be developed over an SC. The DPP is a point that divides the SC into two main parts. The first part, which starts from the upstream side of the SC to DPP, can adopt a lean strategy (with less flection in demand). While from DPP to the downstream side, the companies can follow the agile strategy to deal with customers' needs and requirements.
Mason-Jones et al. (2000b)	Adopting a leagile DP approach to SC re-engineering will guarantee that customer service levels will be enhanced while costs and lead times will significantly diminish. The market winner in leagile SCs is flexibility and responsiveness, which are the principles of agility. Also, the market qualifiers metrics are cost, lead-time, and quality.
Mason-Jones et al. (2000a)	This study verified that SC management based on the leagile strategy empowers managers to design the SC based on market needs. The leagile approach provides leanness and agility features due to the requirements of individual SC. Still, reducing the uncertainty that might lead to the `Bullwhip' effect is crucial.
Agarwal et al. (2006)	Improved SC performance indicates that SC can quickly respond to unstable demand effectively. Leanness and agility in an SC maximise profits by decreasing costs and providing what customers want. The leagile SC enables the supply side of the chain to be cost-effective and the market side to achieve high service levels in an unstable marketplace.
Amir (2011)	He explored the lean, agile and leagile DP to develop a guideline for implementing a leagile strategy. To implement an effective leagile strategy, the SC managers should pay attention to the cultural and technical features. Moreover, the leagile procedure should implement over the entire SC. Leagile strategy should be considered a philosophy of operation management for all decision-making processes in SC (e.g., supplier selection and human resource management).

Naim and Gosling (2011)	They categorised the developments, implementation methods, and concepts of the leagile strategy based on Naylor et al. (1999), presenting the original idea of the leagile strategy. They proposed a framework and guidelines to develop a leagile strategy.
Soni and Kodali (2012)	They analyse the reliability of the leagile strategy in the Indian manufacturing industry. They proposed a model and surveyed to evaluate the effective factors on the success of leagile strategy in the manufacturing industry in India. They deployed principal component analysis to explore the most influential factors.
Purvis et al. (2014)	They develop the flexibility concept as a leagile principle presented by (Naylor et al., 1999). Vendor flexibility and sourcing flexibility are two main dimensions of the flexibility to implement a leagile strategy. For example, customer sensitivity impacts the level of vendor and sourcing flexibility in SC.
Lemieux et al. (2015)	They concluded that a lean transformation should be made through a mixed method, i.e., top-down transformation management. Also, this should be done according to the strategic goals of the businesses.
Nieuwenhuis and Katsifou (2015)	They presented DPP as an effective method for implementing a leagile strategy in the car manufacturing industry by considering the effect of the economies of scale in production. The findings can help companies with low production rates embed sustainable output and control resource consumption.

Shahin et al. (2016)	They demonstrated the advantages of the DPP method for implementing a leagile strategy. They addressed a fuzzy DP to control the distance between leanness and agility.
Galankashi and Helmi (2016)	The operational activities of implementing a leagile strategy have been discussed in their research. They defined the effect of the leagile process on the SCs based on the SCs' drivers. Also, the most important activities were ranked and classified using a MADM technique (i.e., Analytic Hierarchy Process (AHP)).
Haq and Boddu (2017)	This study proposed applying the fuzzy quality function deployment approach to improve the leanness and agility aspects of the SC by recognising the significant enablers. To tackle the uncertainties of judgments in building House of Quality, linguistic variables were used in the form of Triangular Fuzzy Numbers.
Aktan and Akyuz (2017)	They focused on finding the appropriate position of DP in a furniture SC. The DPP is addressed based on the features of different products. Multiple approaches were applied to identify the best DP of a leagile

	strategy under practical constraints. The case study's nature developed a road map for implementing a leagile strategy.
Mostafa et al. (2020)	They followed mixed research methods, including literature and interview. The explored factors which led to an imbalance in the supply and demand side of the housing market by reviewing the literature, such as completion time, cost of a finished house, customer preferences, and level of skilled labour. Then they argued each factor based on the experts' opinions in interviews. The findings confirmed that leagile implementation depends on the identified factors.

Maharaja et al. (2018a)	The results of conducting this literature survey unveiled those efforts are yet to be made to estimate the process of achieving leagility through SCs. Researchers are expected to contribute a model for evaluating the performance of leagile SCs. In this context, this paper ends with proposing the steps to be followed for promoting a leagile SC analysis model. Such a model will benefit the managers to strengthen the weak spots for adopting a leagile strategy in traditional manufacturing companies and gain a competitive advantage.
Maharaja et al. (2018b)	A leagile SC performance analysis model has been suggested in this paper. The model has been extended by consolidating the criteria of leagile SCs into it. The researchers have identified these criteria investigating how to improve the performance of leagile SCs in companies. The mathematical model was used, and interpretation drawn from it by referring to the values derived from it has been represented.
Alinezhad et al. (2019)	A multi-objective optimisation model was developed to make a trade-off between production cost, product delivery time, and customer satisfaction to implement the DPP method.
Mishra et al. (2019b)	They aimed to examine the implementation of leagile strategy in healthcare systems. Their outcomes proved that the other factors, rather than demand and lead-time, should be analysed for implementing a leagile strategy. They deployed MADM methods (i.e., AHP) to rank the most critical factors of leagile implementation in the health care field. While the lean approach is appropriate for oral medicines, the leagile strategy could be adapted for nursing items and food supplements (e.g., insulin, assistive technologies, and diabetic footwear).

Fadaki et al. (2019b)	They proposed a quantitative method for leagile implementation by formulating DPP as the deviation from a balanced leagile. They analyse the effect of imbalance leagile on the total performance of the SCs. In addition, the effect of uncertainty on the deviation of DPP from the balance leagile was examined. The findings confirmed that the level of uncertainty directly and positively affects the Deviation from the Legality index.
Fadaki et al. (2020)	The findings show that most companies choose leagile SC rather than the lean or agile strategy. They emphasised that the companies and SCs can increase their performance by decreeing the deviation of the DPP from the balance point of leanness and agility.

Chapter 3 Research Methodology

3.1 Introduction

A methodology is an approach to a set of steps to finding a solution to the research questions or considered hypotheses. The main aims of conducting the methodology are to show how data are accumulated and to recognise the reliability & validity of the data collected using various methods (Carroll 2014). A methodology is an approach to finding a solution from the research questions or considered hypotheses (Carroll 2014). Different research methods can be used to verify assumptions or obtain information to answer the research questions, including quantitative and qualitative methods. The researcher may inclusively utilise one of these methods or alternately integrate them to certify the research questions or improve the assumed hypothesis (Wisker 2007). There are various criteria to select an appropriate research method, including the nature of the study, objective of the research, method of data analysis, and data collection approaches.

The research methodology is a set of methods, rules, or ideas vital to distinguish an outcome or solution to a particular subject or an issue; this requires a set of procedures to be implemented to reach a robust and reliable conclusion (Saunders et al. 2009). Research methodology can be defined as the steps taken to complete research systematically and solve the research problem. Most of the research methodology presented in SCM is designed based on case studies and surveys. The main reason is attributed to the complex and multi-layered formation of independent companies, which are interdependent. Hence, a survey is designed to answer the research questions and collect quantitative data to investigate this thesis's aims and objectives. The methodological structure of this thesis is based on (Saunders et al. 2009) named “The Research Onion”. This model provides foundational support in detailing the methodological procedures that the researcher needs to consider to achieve the assigned aims and objectives of the thesis. Figure 3-1 shows the research onion methodology, including the selected procedures and choices of data collection techniques to portray the entire processes of the assigned research methodology. Table 3-1 presents the research onion method with selected approaches for this research project, including philosophy, approach to theory development, methodological choice, strategy, and time horizon.

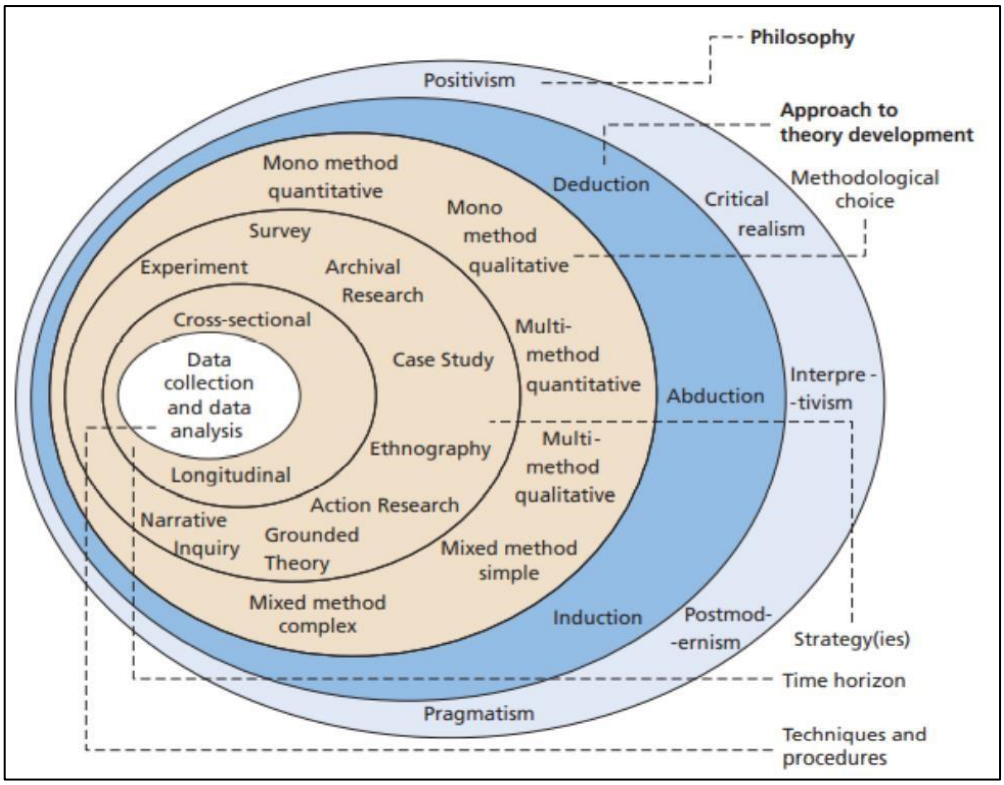


Figure 3-1-The research Onion methodology (adapted from Saunders et al. 2016).

Table 3-1-The selected approaches for this study are based on the research Onion methodology.	
Research Philosophy	Positivism
Approach to theory development	Deduction
Methodological choice	Quantitative
Strategy	Survey/Case Study
Time horizon	Cross-sectional

3.2 Research Philosophy

Research philosophy is based on how data about a particular phenomenon can be collected, analysed, and used (Dudovskiy 2016). Johnson (2006) emphasises that researchers and scholars must be aware of the research philosophy and philosophical commitments throughout the adopted research methodology because it could negatively impact research and performed investigations. According to (Saunders 2014), several research philosophies can be considered to complete the research study, including positivism, critical realism, interpretivism, postmodernism, and pragmatism. However, the two most common paradigms applied to business and management studies are interpretivism and positivism (Saunders et al. 2009;

Thomas 2017). By considering the concept of SC drivers and the proposed conceptual framework, positivism and interpretivism could be the possible research philosophies to select for this study. Hence, the positivism and interpretivism philosophies are explained in the following sections.

3.2.1 Positivism

In the positivist approach, the researcher is independent of the research and study, and therefore, the researcher does not influence the outcome of the findings (Park et al., 2020). The researcher has developed a set of hypotheses and sub-hypotheses through the critical review of the literature. Combining these hypotheses, a theoretical model has emerged as the outcome of the literature review. To test and validate the conceptual model positivistic philosophy and deductive approach have been considered as the most appropriate form of research methodology that fulfils the research aims and objectives (Park et al., 2020).

Positivism is a research philosophy that only trusts the "factual" view or collected knowledge via observations and senses, including measurement. In this philosophy, the central role of researchers is restricted to an objective way to organise and interpret data. The findings and outcomes of positivist research are quantifiable and observable (Park et al., 2020). The positivism paradigm is suitable for research types that require observation to formulate hypotheses or need pre-determined theories for the research (Saunders 2014).

In addition, in the positivist approach, the researcher is independent of the research and study as well as there is not any provision for human interest within the analysis and study.

Crowther and Lancaster (2008) emphasise that positivist studies generally implement a deductive approach, while the inductive research approach is generally correlated with the phenomenology philosophy. In contrast, the phenomenology approach has provided for human interests and concentrates on the meaning rather than facts.

In other words, in the positivist approach, the researcher is independent, which means maintaining minimum interaction with the participants when carrying out your research.

Moreover, investigations and studies using the positivism paradigm are purely considering the facts that believing the world is an objective and external matter.

The five main assumptions and principles of positivism research philosophy can be summarised as follows:

1. No differences in the logic of inquiry across science
2. The aim of the research should predict and explain.

3. The investigation and research must be empirically observable throughout the human senses. Within the inductive approach, the researcher must develop hypotheses to be examined during the research process.
4. Science and common sense are not similar, and common sense should not permit bias in the research findings.
5. Science must be judged by logic only and value-free.

The main element of positivist research philosophy is data or actual observations. In this method, a researcher looks for the casual relationships and regularities in collected data and creates a law-like generalisation. Also, positivist research philosophy employs existing theories to develop hypotheses that are examined, confirmed, or referred for further development of theories by further investigation (William and James 2006).

This research is vigorously categorised as a positivism study because the hypotheses were developed according to the facts gained from the knowledge, testing hypotheses and sub-hypotheses using the empirical data, analysis of accumulated data to measure the results and ability to classify and codify the outcomes as a set of predictions or laws. In addition, in this study, the other characteristics of the positivist approach including using a quantitative method such as surveys, questionnaires, and interviews were applied due to their higher representativeness and reliability of these methods.

3.2.2 Interpretivism

According to O'Reilly (2009), interpretivism directs to theories and epistemologies about collecting knowledge and data from the world, which freely relies on understanding and interpreting the concepts humans attach to their behaviours and actions. Saunders (2014) states that interpretivism relies more on subjective interpretations than objective. Interpretivism provides meaning to the environment using “Symbolic” and “Phenomenology”. The symbolic is a continuous process of interpreting the social world, while phenomenology directs to the means humans understand the world. Interpretivism is applied to analyse the actions, which creates and adjusts the meanings of others’ actions (Saunders 2014). Also, it investigates the entire business's abilities to identify the environment and adopt the obtained strategies. Hence, interpretivism is more suited to organisational behaviour (corporate culture) and human resource management studies but not the current study where the causal relationship between the factors of SCs within industrial clusters in being investigated (Saunders 2014).

In conclusion, by considering the nature of the current research domain and scopes of this study to determine the measurable and quantifiable relationships between the SC drivers, DPP and TSCV factors in the existing moderators, the conceptual framework of this study was defined based on the established theories. Hence, it is required to examine the proposed hypotheses by collecting actual data from the applicants, which shows strong evidence of the positivism research paradigm for the research philosophy.

3.3 Approaches to theory development

According to theories of research methodology, there are three typical procedures to conduct the research, including deductive, abduction, and inductive approaches, when the researcher will concentrate on real/actual events and use them to develop new theories centred on qualitative data findings, known as the inductive approach. In contrast, the deductive process involves formulating a hypothesis and collecting empirical data to evaluate the applicability of the theory or model for the case study (Bryman and Bell 2011). Furthermore, the abductive approach referred to address the weaknesses associated with inductive or deductive methods. In this case, the abductive research approach starts puzzles or surprising facts which the research process attempted to explain it. The surprising facts might be raised to meet an empirical or experimental phenomena which cannot be explained by the existing range of theories (Bryman and Bell 2015).

The deductive approach is a reasoning method which works from general to the more specific and informally called a top-down method. In this method, the theory must be thought or derived from the research interests, knowledge gaps, or preceding literature review. The next step is extracting specific hypotheses from the main research question or principal theory. Then the data and observations will be collected based on the developed questionnaire or survey and proposed hypotheses. The accumulated data will be tested to determine whether the proposed hypotheses may accept or reject using appropriating testing approaches.

On the other hand, the inductive approach moves from observation and collecting data to generalise the theory and informally named a down-to-up approach. In this method, the specific observation measures frequently to detect a particular pattern or formulate the tentative hypothesis.

In this study, considering the preceding literature review and development of the construct, five main hypotheses were developed and tested to determine whether the developed main hypotheses and their sub-hypotheses were accepted or rejected. Hence, the selected research

approach for this study is a deductive method, and the inductive method is unsuitable for this research.

3.4 Methodological Choice

Fundamentally two methodological choices are available for the researchers to collect or generate data for the research, including qualitative and quantitative. However, Saunders (2014) introduced several combination approaches, including mono method qualitative, mono method quantitative, mixed methods simple, mixed methods complex, multi-method quantitative, and multi-method qualitative. The phrase "mixed methods" refers to advanced methodology research created by mixing or systematically integrating two primary research methodologies, including quantitative and qualitative, within a sustained inquiry or single investigation program. The mixed-method research initiated in social science research has recently extended to health and medical science, including family medicine, nursing, social work, mental health, pharmacy, and other areas (Wisdom and Creswell 2013).

"There are differences between quantitative and qualitative research in terms of research strategy, and many researchers and writers on research methodology perceive this to be the case" (Bryman and Bell 2011).

Using statistical methods, the quantitative approach illustrates a clear and precise way to analyse the numerical data. This approach relies on collecting arithmetical data by conducting various mediums such as observing tests, surveys, and questionnaires centred on hypotheses or theories. However, the qualitative approach focuses on collecting and analysing the hypotheses based on the state and adjective of the events or phenomena instead of the numbers. There are various methods to obtain qualitative data, such as organisational stories, focus groups, case studies, questionnaires (semi-structured or structured), interviews (open, structured, or semi structured), discourse analysis, ethnographies, participant observation, and life/career histories (Fisher and Buglear 2010).

This study applied qualitative and quantitative methods to collect data (via a survey) and analyse them via statistical methods. The qualitative approach was used while interviewing the experts (7 experts in total) to improve the validity of the questionnaire. At the same time, the quantitative strategy was considered to conduct the survey and collect the data to verify the main hypotheses of the thesis. Three main steps were considered to evaluate the hypotheses for this study:

- Produce a survey based on the hypothetical structure, including four main SCs' drivers and their interlinking on the LSCS and TSCV.
- Collect empirical information using a questionnaire from the selected companies.
- Critically evaluate the significance of the experiential data on the initial hypotheses using statistical methods.

3.5 Research Strategy

A research strategy is a definitive plan in which a researcher considers answering the set of questions and objectives to achieve the aim of the study (Saunders 2014). Denzin and Lincoln (2011) state that research strategy is the methodological link between the selected philosophy and chosen method to accumulate and analyse data. Several strategies can be selected to carry out the research, including archival research, grounded theory, experiment, case study, and survey (Crotty 2020). In addition, Saunders (2014) added other research strategies, including action research and documentary, ethnography, and narrative inquiry. Although each research strategy has advantages and disadvantages, a survey is a prevalent and common method applied in business and management studies (Crotty 2020). Furthermore, a survey strategy is generally mixed with a deductive approach, allowing a researcher to collect several data samples of appropriate sizes (Bell et al. 2018). Survey and case study approaches were selected in this study because they are harmonised with the purpose, objectives, and limitations.

3.5.1 Case Study Method

There is a lack of rigour and consistency when a certain number of case studies have been used because the acquired data through the case studies could be affected by specific parameters or factors. (Yin 2003). The most critical parameters affecting the data acquisition include ambiguous questions, dubious evidence, and disorganised procedures. Furthermore, the personal opinions of data collectors, sense, mode of questioning, or pre-assumed considerations of researchers could affect the acquired data and, therefore, the achieved outcomes. Yin Yin (2003) suggests that the reliability of the case study would be enhanced by eliminating personal emotions and avoiding bias while providing the technical report from the accumulating evidence. In addition, he believes that the researcher would remain open-minded and not generalise observations and findings across all over the various case studies.

On the other hand, many scholars emphasised the advantages of using the case studies method within the primary data collection. They argued that the evaluation and analysis of complex

phenomena with numerous inputs and variables could be achieved (Hox and Boeije 2005; Noor 2008).

Primary data can be defined as data accumulated directly from the initial source, whereas a third party proposes secondary data after its accumulation (Hox and Boeije 2005).

Although, collecting the primary data is very time-consuming, relies upon the selected case studies, and restricts the number of cases. Nevertheless, the results and conclusions are more reliable and valid than the secondary data.

This study mainly collects primary data directly from the employees of three supply chain clusters, including 260 research participants. They are currently working for the main furniture, agricultural machinery and equipment, and trout fish clusters in the North of Iran. In addition, the assumed research questions were answered by accumulating information using a quantitative approach. The selection of an appropriate case study was crucial to reflect and explore the assumptions of this study. Table 3-2 shows the number of participants who contributed to this study from the three supply chain clusters.

Table 3-2- The number of participants who contributed to this study

Supplier	Manufacturer	Distributor
38	164	58

3.6 Time Horizons

A time horizon can be defined as a time framework of research that proposes or plans the start and end of the research study (Saunders 2014). Larry et al. (2014) stated that the time horizon could be in a sequence of snapshots over a certain period called longitudinal research or carried out in a specific time named cross-sectional research. Although longitudinal research is more time-consuming, the main advantage of this type of research is evaluating and analysing the development and change of research. At the same time, the cross-sectional research attempts to describe how factors are related in different organisations in a specific period, matching well with the research aims and objectives of this study. The cross-sectional perspective is less time-consuming than longitudinal research (Saunders 2014).

3.7 Rating Scales

The rating scale is a closed-ended survey question or variant of the multiple-choice question, broadly applied to collect information and data for a specific topic. Researchers and scholars used rating scales in their studies to associate a qualitative measure with the various aspects of

a feature or product. Tull and Hawkins (2003) stated that the rating scales help the researcher examine approaches and attitudes presented in the standard questionnaire to collect data. Several scaling techniques can be applied for research; nevertheless, the main three rating scales are the Stapel scale, Semantic differential scale, and Likert scale (Bryman and Bell 2011). The Semantic differential scale is bipolar, meaning two sides of a point stand.

On the other hand, the Stapel scale is considerably different, which has a unipolar scale with ten sets of points or opinions (Louviere et al. 2013). The Likert scale is a significantly different method to collect applicants' opinions because the questions are asked from the participants regarding attaining their agreement or disagreement with the given or predefined statements (Saunders 2014). In survey strategy, the Likert scale is the most appropriate method when asking respondents' attitudes towards a particular subject or topic. This scale is also widely employed when researchers explore consumer psychology (Louviere et al. 2013). Due to the nature of this study, the Likert scale is considered for the research questionnaire.

3.8 Ethical Consideration

Ethical concerns and issues must be considered before collecting data and distributing the research questionnaire (See Appendix 5: Questionnaire and invitation form). Bryman and Bell (2011) considered several possible principles of ethical concerns, including inappropriate communications, avoiding deceptive and misleading information, and protecting applicants' privacy. Hence, all these elements and codes were noticed and implemented via completing the ethical checklist, then examined and approved by Bournemouth University's central research ethics panel. According to Bournemouth University's policy and its ethical procedure in research, all conducted studies involving human participants at the Business school must have written approval from the Research Ethics Committee (REC) at Bournemouth University. The questionnaire and all relevant documents were submitted to REC, and ethical permission was granted on the 3rd of August 2020 (See Appendix 6: Ethics approval notice). Furthermore, collecting data was performed based on the willingness of participants' views, which allowed applicants to withdraw from the survey. Before disseminating the survey, all applicants were informed about the reason behind the study, the survey's timeline, and the author's role and responsibility.

3.9 Research Design

Gray (2019) highlighted three primary research forms exploratory, descriptive, and explanatory. The first two forms seek to explore a problem upon knowledge of a limited number of experts

and descriptively provide a big picture of the problem. The explanatory forms focus on discovering the cause-effect relationship variables for a phenomenon and further analysing how they affect each other (Rovito and Rhodes 2016). Kumar et al. (2019) showed that after defining the dimensions of a research problem and developing an appropriate research methodology, a researcher should focus on constructing tools for collecting and analysing data. The main goal of the research design is to outline how to answer research questions. Sekaran and Bougie (2016) presented six steps for doing research, including research characteristics, investigation taxonomy, research unit, research time, research setting, and interference of the researcher and the participants.

3.9.1 Investigation Taxonomy

Sekaran and Bougie (2016) defined two investigation categories: correlation and causal. The causal investigation establishes the research questions to generate a distinct cause and effect relationship. Usually, in causal analyses, several factors are recognised for constructing the associations (Sekaran and Bougie 2016). According to the research model of this study, causal investigating is deployed to analyse the relationship among supply chain drivers, leagile strategy, industrial clusters' factors, and supply chain performance.

3.9.2 Research Unit and Scope of Research

The research unit is the scope of the investigation in a study and for which data is collected (Sekaran and Bougie 2016). The research unit could be an organisation, a group of organisations, a section, or a country. According to the goals of this study (i.e., evaluating the effect of leagile strategy on the performance of supply chain in industrial clusters), the research unit would be the organisations within three industrial clusters, including furniture, agriculture machinery and equipment and trout fish in Mazandaran province, Iran.

The researcher has selected three industrial clusters to ensure that the study is representative and comprehensive of the industrial clusters in Mazandaran Province. Three industrial clusters have been selected to analyse the opportunities of implementing a leagile strategy in a developing country, Iran. Also, the two clusters were selected from agri-food supply chains. The performance of the agri-food supply chain not only significantly impacts the country's food security, human well-being, land use, and climate change but is also vital for the global agri-food ecosystem. Selecting Iran for this study can have a higher impact because of the unique challenges and opportunities, relevance to a broader audience in developing countries, potential for positive impact, and opportunity to address under-studied issues. By focusing on developing countries, the study can significantly contribute to developing knowledge in the

field of supply chain strategies and improving policies and practices that can positively impact the lives of people in these countries. The main reasons for selecting these three industrial clusters in Iran are as follows:

- Unique Challenges and Opportunities: Developing countries often face unique challenges and opportunities that are not present in more developed countries. Studying these challenges and opportunities can provide valuable insights into addressing them and highlight innovative approaches that might be relevant to other countries (Fine et al., 2016).
- Relevance to a wider audience: Developing countries often represent a large and growing portion of the global population. Many of the challenges they face are also relevant to other countries. As such, studies of developing countries can have broad implications for policymakers, practitioners, and researchers in other parts of the world (Forestier and Kim, 2020, Morris et al., 2020).
- Potential for Positive Impact: The challenges faced by developing countries can often profoundly impact the lives of people in these countries. By studying these challenges, researchers can contribute to developing solutions that can positively impact the lives of people in these countries (Aly, 2022).
- Opportunity to Address Under-Research Issues: Developing countries are often under-studied, particularly in certain research areas. By conducting this research in Iran, I have the opportunity to contribute to developing supply chain knowledge there and address important questions that have been overlooked in previous studies (Shaner, 2019).

Meanwhile, this study, for the first time, analyses the impact of the supply chain drivers on the DPP in the context of industrial clusters. The industrial cluster unit has been selected based on the following reasons:

- Improved competitiveness: Understanding the characteristics of an industrial cluster and its competitive strengths and weaknesses can help companies within the cluster improve their competitiveness and better position themselves in the marketplace (Hsu et al., 2014).
- Better Coordination and Cooperation: Industrial clusters often bring together companies from different parts of the supply chain and support industries and institutions. A cluster analysis can help identify opportunities for coordination and cooperation between firms and institutions, which can lead to improved productivity, innovation, and competitiveness (Lorenzen, 2001).

- Improved Policy Making: Analysis of industrial clusters can provide valuable information for policymakers, who can use this information to design policies that are better suited to the cluster's needs and its companies' needs. This can help ensure that policies effectively promote growth and competitiveness (McDonald et al., 2006).
- Improved Innovation: Industrial clusters often have a high concentration of companies, institutions, and resources that can support innovation. An analysis of the cluster can help to identify the key drivers of innovation and to determine how to support better and leverage these drivers for the benefit of the cluster and its companies (Turkina, and Van Assche, 2018).

This study addressed the research questions and objectives by surveying companies within three industrial clusters: furniture, agricultural machinery and equipment, and trout fish. Not only are these clusters form the largest industrial clusters in the Mazandaran province, but also, they face many challenges as follows (Ernst et al., 2001, Munnich et al., 2003, Saadatyar et al., 2020):

- High Cost of Production: Agricultural machinery and equipment can be expensive, especially for small-scale farmers, as customers may not have the resources to invest in new technologies. This can limit the adoption of new technologies and make it difficult for companies to improve their productivity and competitiveness.
- Lack of Technical Expertise: Agricultural machinery and equipment often require specialised technical knowledge and skills to manufacture the products. This can be a challenge for companies in developing countries that may not have access to technical training or support.
- Inadequate Infrastructure: In many developing countries, there is a lack of adequate infrastructure, such as roads, bridges, and storage facilities, which can make it challenging to transport raw materials within the supply chain.
- Limited Access to Finance: Small and Medium size companies in developing countries often face significant challenges in accessing financing to establish supply chains. This can limit their ability to invest in new technologies and improve their competitiveness.
- Limited Availability of supplies: The limited Availability of supplies can make it difficult for companies to manufacture their machinery and equipment, leading to increased downtime and reduced productivity.

- Seasonal Fluctuations: products are often subject to seasonal fluctuations, which can result in demand changes. This can make it challenging for manufacturers and suppliers to plan production and manage their supply chains effectively.

Based on the above reason, this study addresses the research objectives in 1) a developing country, i.e., Iran; 2) select units as industrial clusters; 3) select three significant industrial clusters, including furniture, agricultural machinery and equipment, and trout fish.

3.9.3 Research Time

In this study, data would be collected only once. According to the type of research, there is no reason for collecting data with a predefined interval (longitudinal research time). Hence, this research is categorised as cross-sectional based on the time aspect (Sekaran and Bougie 2016).

3.9.4 Research Setting

Sekaran and Bougie (2016) classified research into field study, field experiment, and lab experiment according to the types of investigation and researcher interference. The research is known as a field study if the researcher only asks the respondents to give their idea and does not let them make any changes. A field experiment is when the researcher changes explanatory measures in the field experiment class to examine their effect on the response variable. Finally, the causes-effects relationship is tested in the lab experiment. Since the respondents cannot change the questionnaire, this research falls into the field study taxonomy.

3.9.5 Researcher Interference

Sekaran and Bougie (2016) specified that the researcher's interference level with the current workflow within the research unit directly depends on the investigation category. In this study, the researcher has no interference in the workflow.

3.9.6 Measurable and observable variables

After developing the constructs and hypothesis, measurable and observable variables should be employed to analyse the proposed conceptual model. Then the questionnaire would be designed based on the defined measures. This section identifies the measurable and observable variables for the research model, including Decoupling Point Position (DPP), supply chain drivers, industrial clusters factors (including basis and foundation, business and enterprise, and market), and Total Supply Chain Value (TSCV). In addition, all questions would be measured based on the 6-point Likert scale ranging from strongly disagree (0) to strongly agree (5).

i. **Decoupling Point Position**

Table 3-3- Questions to measure the DPP factor of leagile strategy.	
Code	Questions
DPP1	The main production approach of the company is designed to respond to all market needs.
DPP2	The main production approach of the company is designed by considering the maximum efficiency to decrease costs.
DPP3	The main inventory management of the company focuses on holding work in process products rather than the final product.
DPP4	The main inventory management of the company focuses on holding final products rather than work in progress.
DPP5	The company's supply chain distribution policy focuses on distributing products according to the market's demand.
DPP6	The company's supply chain distribution policy focuses on distributing products to the market after receiving the actual demand from the market.
DPP7	The company's supply chain shares information from downstream to upstream and vice versa.
DPP8	The company only shares information with limited partners in the industrial cluster.

ii. **Supply chain drivers – Production:**

Table 3-4-Questions to measure production factors as supply chain drivers	
Code	Questions
Pro1	Products' due dates are short in the company.
Pro2	The product cycle time is short in the company.
Pro3	The production variation cost in the company is high.
Pro4	The demand for products is high in the company.
Pro5	The production utilisation rate is high in the company.
Pro6	The company's products are designed to have maximum performance and minimum cost.
Pro7	The company reduces any kind of waste as much as possible.

iii. **Supply chain drivers – Inventory:**

Table 3-5-Questions to measure inventory factors as supply chain drivers.	
Code	Questions
INV1	The high volume of raw materials holds in the company.
INV2	Low volume of final products holds in the company.
INV3	The demand is rather constant for final products in the company.
INV4	The order point is rather fixed in the company.
INV5	The inventory holding cost of the final products is high in the company.
INV6	Inventory turnover is high in the company.

iv. **Supply chain drivers – Location:**

Table 3-6-Questions to measure location factors as supply chain drivers.	
Code	Questions
Loc1	The appropriate location of the company led to decreased costs, including land, energy, transport infrastructure, business services, telecommunications, and labour.
Loc2	There is appropriate infrastructure in terms of land, energy, transport, and telecommunications, due to the location of the company.
Loc3	The suitable location of the company has enhanced your access to business services such as air, sea, and land transport services, financial services, legal services, and information technology.
Loc4	The suitable location of the company increases the availability and quality of labour education and skill.

Loc5	The company's location within the industrial cluster provides government and tax policy stability.

v. **Supply chain drivers – Information:**

Table 3-7-Questions to measure Information factors as supply chain drivers.	
Code	Questions
Inf1	The company to share more accurate information with its partners within the industrial cluster to respond to customers' changing needs.
Inf2	The company have built a partnership with a few partners within the industrial cluster to share more accurate information to reduce supplier uncertainty.
Inf3	The development of IT provides numerous opportunities for your company to increase the level of information sharing within an industrial cluster.
Inf4	The rapid development of IT technology forces your company to share more accurate information with partners in the industrial cluster.
Inf5	Top management/coordinator of your industrial cluster support companies in sharing information with other partners through the supply chain.
Inf6	Top management of the company supports your company in sharing information.
Inf7	IT enables the company to open new opportunities for increasing value through information sharing within the supply chain.
Inf8	Trust among the partners within the industrial cluster has removed obstacles to information sharing between partners.
Inf9	Partner's commitment within the industrial cluster leads the company to share accurate information, which indicates a high level of information sharing.

vi. **Supply chain drivers – Transportation:**

Table 3-8-Questions to measure transportation factors as supply chain drivers.	
Code	Questions
Tran1	Products and raw materials are delivered quickly among company partners within the industrial cluster.
Tran 2	The company's transportation system fulfils promises to consignees.
Tran 3	Transportation proficiencies improve the utilisation of facilities/equipment/workforce in providing the company's services.

vii. **Industrial clusters basis and foundation:**

Table 3-9-Questions to measure the basis and foundation factor in the industrial cluster.	
Code	Questions
Bas1	Skilful employees are working in the company.
Bas2	The company has a high net working capital (financial resources).
Bas3	The company secures growth and revenue from industry sectors characterised by new and rapidly changing technology.
Bas4	The company considers technological innovation and R&D to improve its innovation capacity.
Bas5	The company has an excellent communication infrastructure for communicating with other companies in the industrial cluster.
Bas6	The company has a great deal of control over its external environment.
Bas7	The company has a great deal of control over its internal environment.
Bas8	The company has adequate training and development policy.
Bas9	The company has a high degree of work specialisation.
Bas10	Rules and regulations of the company occupy first place in the organisational structure.

viii. **Industrial clusters business and enterprise:**

Table 3-10-Questions to measure business and enterprise factors in the industrial cluster.	
Code	Questions
Bus1	There are strong suppliers within the company's industrial cluster.
Bus2	There is strong cooperation among the companies in the industrial cluster.
Bus3	There are reliable companies within the industrial cluster.
Bus4	There are honest companies within the industrial cluster.
Bus5	Companies cooperate within the industrial cluster.
Bus6	There are strong competitors within the industrial cluster.
Bus7	All members have compiled the rules of the industrial cluster.
Bus8	All members align with the goals of the industrial cluster.

ix. **Industrial clusters market:**

Table 3-11-Questions to measure market factors in the industrial cluster.	
Code	Questions
Mark1	The company follows constant sale policies within the industrial cluster
Mark2	The demand for the company's products is high in local markets
Mark3	The company has a positive outlook on the future of local markets
Mark4	The company connects to the local value chain of its products
Mark5	The distance of the company to foreign markets is short
Mark6	The company has a positive outlook on the future of global markets
Mark7	There are no obstacles and limitations to foreign markets for the company within the industrial cluster
Mark8	The demand the foreign markets is high for the company

x. **Total Supply Chain Value:**

According to (Gunasekaran et al. 2004), many SCs haven't maximised the potential of their chain's capabilities due to failure to adapt suitable metrics to evaluate their SC's performance. Naylor et al. (1999a) identified the four-performance metrics, including lead-time, service, cost, and quality, to assess the performance of an SC. Figure 3-2 shows the metric of total supply chain value.

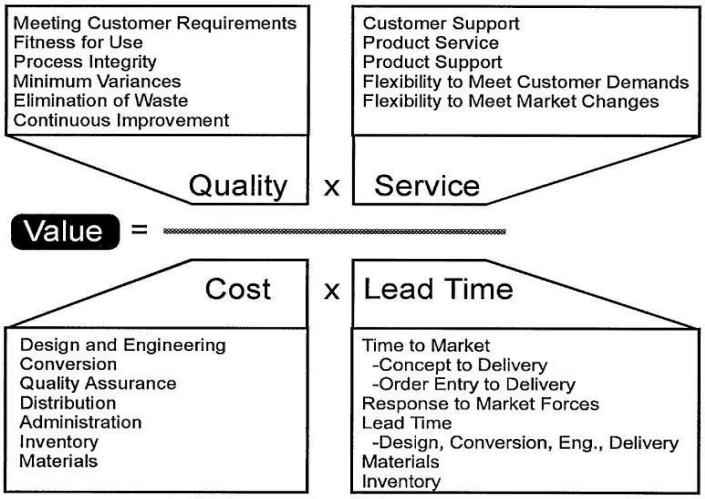


Figure 3-2- Total Supply Chain Value (TSCV) Metric (Mason-Jones et al. 2000a).

There is extensive literature on SC dealing with supply chain performance metrics and competitive advantages. Indeed, scholars have aimed to identify the optimal SC performance

metrics according to the nature of SC's product types and other SC features. For instance, ArifUz-Zaman and Nazmul Ahsan (2014) presented supply chains' time, cost, quality, and flexibility metrics for evaluating high volume, low-price products under the lean strategy. Shepherd and Günter (2010) addressed the shortage of studies on the performance metrics of SCs by reviewing the literature and suggesting possible avenues for future research. They argued that scholars should pay more attention to the SCs' performance metrics and measurement systems and evaluate the metrics' effectiveness for different SCs (Shepherd and Günter 2010). Maestrini et al. (2017) reviewed the SC performance metrics literature and presented the necessity of evaluating the performance of the SC by considering different drivers of the SCs. This study attempts to evaluate the effect of the LSCS on the SCs' drivers and further on the TSCV based on the four-performance metrics, including quality, service, lead-time, and cost. Table 3-12 shows the assigned questions to measure TSCV in this study.

Table 3-12- Questions to measure Total Supply Chain Value.

Code	Questions
TSCV1	How well does the company perform relative to its competitors in terms of cost?
TSCV2	How well does the company perform relative to its competitors in terms of quality?
TSCV3	How well does the company perform relative to its competitors in terms of lead-time?
TSCV4	How well does the company perform relative to its competitors in terms of service?

3.10 Data collection

The survey questionnaire has been developed according to the measurable and observable variables. The following four parts are considered for designing the questionnaire.

3.10.1 Questionnaire Development

Although the main method to acquire primary data from the cluster of SC is considered the survey, the questionnaire form has been checked and assessed by interviewing the local experts to ensure the questions' consistency, validity, and quality.

The literature review explored well-known and commonly used factors for effectively implementing LSCS and the SCs' drivers and performance metrics. The questionnaire would help this study to first collect the data related to the position of the clusters in the north of Iran

according to the LSCS factors. Also, the questionnaire would be used to collate the value of each factor, driver, and metric relative to the other one according to the proposed construct. In this manner, the questionnaire comprised of two parts: the position or situation of LSCV factors, SCs' drivers, and SCs' performance metrics and the relative importance of each item compared to the other items. The designed questionnaire is shown in Appendix II. Researchers in the SC managers widely use the 6-point Likert scale or similar Likert scale to simplify the survey method and increase the data collection rate (Saaty and Vargas 2006; Saaty and Cillo 2008). The questions and options were estimated through respondents' perceptual evaluation on a 6-point Likert scale as summarised in Table 3-13- The Likert scale (0 to 5). Several researchers applied a 6-point scale used zero to five Likert scale in their studies due to provide a rational reason to omission o eliminate the mid-point in the questionnaire survey (Wang et al, 2000; Wang et al. 2004; Gandhi et al., 2016; Shipley, Cao, & Davis 2017; Adafin et al., 2020; Ghode et al. 2020). Response to this type of questionnaire provides an interval scale characteristic to the measuring scale and makes the collected data more suitable for the various statistical data analysis (Ling et al. 2000; Kululanga et al. 2001; Odeyinka et al. 2008; Chileshe, and Yirenkyi-Fianko 2012).

Table 3-13- The Likert scale (0 to 5) used for the SC and TSCV variables.

Intensity of Importance	Definition for all variables	Definition for TSCV
0	Strongly Disagree	Much Worse
1	Disagree	Worse
2	More or less Disagree	Somewhat Worse
3	More or less Agree	Somewhat better
4	Agree	Better
5	Strongly Agree	Much Better

3.10.2 Validation of the Questionnaire by Interviewing Experts

The validity of the questionnaire concerns the extent to which an instrument measures and what it intends to measure. (Nascimento-Ferreira et al. 2018). Hence, before conducting the survey, two sets of interviews were assigned to seven SC experts to improve the quality and validity of the questionnaire. Within the interview, the main goals of the research, the findings from the literature, the proposed hypothesis, and developed constructs were explained to the experts. According to (Goldie and Pritchard 1981), there are three types of interview methods to collect

personal experiences and professional opinions from interviewees known as unstructured, semi-structured, or structured interviews. In addition, Bryman and Bell (2011) state a 38% possibility of raising new questions during a qualitative-unstructured interview. Therefore, this approach is more flexible and leads to amendments to the questionnaire form. The questions in a structured interview, embedded in a quantitative methodology, are fixed and cannot be changed. Any answers that would not fit the study could be considered noisy data and ignored. Furthermore, within certain studies, the questions and answers are standardised to increase the validity and reliability of the structured interview (Bryman and Bell 2011).

Unstructured interviews are extensive because there is no script or fixed questions within the discussion. The interviewee may define a general theme for the interview, and a conventional conversation may occur. This interview form is utilised when the researcher searches for a general sense of the interviewee's thoughts and opinions without guiding them with their agendas (Bryman and Bell 2011). However, if there was an existing theme in which a researcher must focus on the subject, the semi-structured interview is the most appropriate type. Within the semi-structured interview, the interviewer would concentrate on the opinions and interests of the interviewee, which allowed the topics or sub-topics to be discussed, expanded, and ultimately guided by the interviewee. Consequently, the given answers by the interviewee become more natural and tend away from the researcher's question, leading to the elimination of the researcher's agenda.

Hence, the semi-structured interview was selected for this study to check the quality of the survey, avoid any ambiguity in the questions, and enhance the consistency of the questionnaire before conducting the survey. Furthermore, Bryman and Bell (2011) state that the reliability of the obtained opinion is increased with this form of the interview when multiple scholars are involved in the interviews. As discussed, the semi-structured interview helps to enhance the questionnaire's overall quality by reflecting the expert's feedback and opinion without restrictions on the questions. For this study, seven specialists from SC drivers were selected to conduct the semi-structured interview and assess the questionnaire.

The method of executing the interviews was face-to-face to increase the quality of the procedure. The interview duration would be between 1.5-2.5 hours per meeting. The total time for the discussions was estimated to be around 14 hours. Initials were applied due to privacy requests from the interviewees for all technical reports and publications. The interviews would be conducted in a calm environment with minimal interruptions and distractions to create a more comfortable environment where the interviewee will more likely give accurate answers.

In addition, native language was considered. Since the developed questionnaire is comprised of two parts, the main survey will be conducted to evaluate the hypotheses of this thesis.

3.10.3 Participant

The participant part describes the details of the study, including the research title, the researchers' contact information, the research institution, and the research objectives and questions. Then participation procedure is presented, consisting of a guideline on how to fill the questionnaire, the expected time of completion, the number of questions, and the measuring scale (6-point Likert scale). Finally, the researcher has emphasised that there are no risks or benefits in the research and anonymity and confidentiality of responses and participants' rights will be preserved.

3.10.4 Panel Selection

Screening questions would be deployed to guarantee only appropriate and skilled experts complete the questionnaire. Therefore, the potential experts who are not qualified were removed from the panel. Screening questions are as follows:

- Do you have a role in configuring your company's industrial cluster?
- Do you have a role in coordination with the upstream and/or downstream side of your supply chain in the industrial cluster?

Respondents would be eligible and qualified if they answered 'Yes' to the screening questions.

3.11 Data Analysis techniques

3.11.1 Confirmatory Factor Analysis

Confirmatory Factor Analysis (CFA) is a quantitative method that can be applied to verify the structure of a set of observed variables. CFA helps the researcher test the proposed hypothesis with an inter-relationship between the observed variables and their underlying latent constructs (Hussain et al. 2016). CFA is a structural equation modelling (SEM) technique to analyse the relationship between measures and factors (Khan et al. 2019). Many scholars applied the CFA method to evaluate the impacts of the factors on the performance of the SCs (Khan et al. 2019). For instance (Zhang et al. 2006) used CFA to analyse the effect of flexibility on enhancing the value chain of SCs. They collected data from 273 manufacturing executives and applied the CFA method as a tool for structural equation modelling (Zhang et al. 2006). Wang and Ahmed (2004) focused on the measurement constructs of organisational innovativeness. They identified five dimensions of an organisation's overall innovativeness and tested their construct's validity using CFA (Wang and Ahmed 2004). Hence, the CFA can analyse and validate the supply chain constructs based on structural equation modelling (Habidin et al.

2015). Therefore, this study proposed two constructs of LSCS and SC's drivers and TSCV and applied CFA to validate them.

3.11.2 Structural Equation Modelling (SEM)

Structural Equation Modelling (SEM) comprises a set of comprehensive multivariate techniques to examine hypotheses that link between variables (i.e., unobserved variables) and observed variables (i.e., measured) (Hoyle 1995). Rigdon (1998) stated that SEM is a methodology that tests, estimates, and represents a theoretical network of the linear relationship between variables. Byrne (2013) also specified that SEM is a statistical approach mainly applied to confirmatory factor analysis rather than exploratory analysis.

According to (Byrne 2013), the SEM approach has three main advantages compared with other multivariate techniques (multiple regression, conjoint analysis, and multivariate analysis of variance). The SEM technique can assess measurement error for independent and dependent variables, while most traditional multivariate approaches inadvertently ignore measurement error by not using explicit modelling. Furthermore, the SEM analysis can estimate the variables (unobserved values) by using observed variables. Also, the proposed constructs can be tested against the data using SEM. A model can be imposed and evaluated to fit the collected data (Byrne 2013).

There are typically two methods to measure the parameters of SEM, including the variance based (i.e., component-based) method and the covariance-based approach (CB/SEM) (Haenlein and Kaplan 2004). Usually, the term 'SEM' is used for the covariance-based approach, in which several software packages are available to conduct covariance-based analysis, including LISREL, COSAN, SEPATH, EQS, and AMOS.

On the other hand, if the covariance-based extends to its restrictions and limitations, variance-based SEM would be applied to analyse the model. The Partial Least Squares (PLS) path modelling is one of the well-accepted approaches developed based on the variance-based SEM to assess a construct and its hypotheses. The PLS path analysis is appropriate for a small sample size. Different software packages are available to assess a construct based on variance-based technique (i.e., PLS/SEM), including PLS graph and Smart PLS (Haenlein and Kaplan 2004).

Determining the most appropriate sample size for the SEM analysis is critical due to the inconsistency in the literature review to identify the best SEM approach for the collected sample size. Some research indicated that simple SEM constructs might be practically tested even if the sample size (N) is relatively small (Hoyle 1995; Marsh et al. 2011). Most researchers consider a small sample size (N) from 100 to 150 observations (Anderson and Gerbing 1984;

Tinsley and Tinsley 1987; Ding et al. 1995). Other researchers consider a larger sample size (i.e., N=200) (Hoogland and Boomsma 1998; Kline 2005).

Muthén et al. (2018) examined various studies using the simulation-based method to determine a reasonable sample size for a simple CFA model. Their studies demonstrate that N=150 observation is enough for normally distributed data without missing observations.

Kline (2005) stated that for the multi-group modelling, the rule of thumb showed 100 observations (i.e., cases) per group required to complete a reliable SEM analysis. Novikova et al. (2013) suggested that SEM requires a minimum of 200 sample sizes to evaluate a basic model, while the complex models might require larger samples to achieve statistical power.

Most researchers have referred to the rule of thumb, which shows a minimum of ten observations per indicator required to complete the covariance-based SEM analysis.

Munim and Schramm (2018) considered the impacts of logistics performance and port infrastructure on economic growth for 91 countries with seaports. They applied the variance-based SEM analysis by collecting 228 observations for their complex construct. They found that developing countries must improve port infrastructure quality continuously.

Green et al. (2019) studied the supply chain management (SCM) model to develop an empirically assessed construct within its operation. They defined 83 indicators or measures for their construct while collecting data/observations from 136 United States manufacturing companies via an online survey. According to the rule of thumb, their sample size (N) is significantly lower than ten observations per indicator; hence they applied a partial least squares structural equation modelling (PLS/SEM) to assess the efficacy of the theorised model using WarpPLS 6.0 software.

Fadaki et al. (2020) conducted quantitative research on hypercompetitive and dynamic business environments. They applied variance-based SEM analysis (PLS/SEM) to analyse collated data from 299 Australian companies.

Rehman Khan and Yu (2021) conducted a study to evaluate the eco-environmental performance using a variance-based SEM approach via Smart PLS software to test their hypothesis. They collected data from 415 manufacturing companies. They concluded that the green information systems and internal environmental management strongly and positively influence the execution of green supply chain practices.

Inman and Green (2018) studied the influence of green supply chain management practices and lean manufacturing on environmental performance using PLS/SEM and CB/SEM approaches.

Their results demonstrated that although there is a slight difference between statistical results, the two analyses' remarked conclusions are the same. The minor differences between the statistical values do not change the boundary of the findings.

Finally, the preceding literature review asserted that PLS/SEM was a well-suited approach for hypothesis testing, prediction, and maximising the variance explained by dependent latent construct (Hair et al. 2011; Matthews et al. 2018).

For the current study, the defined research construct consists of five SC drivers and three moderators' variables, including 67 indicators (i.e., measures or items). To conduct covariance-based SEM (CB/SEM) for the proposed construct, it would be essential to collect a minimum of 670 observations (10 observations per indicator).

While in this study, 212 applicants replied to the survey successfully, showing that the collected data and number of samples are insufficient to conduct the CB/SEM analysis. Hence, the PLS/SEM has been selected to analyse the proposed construct for this study.

3.11.3 Limitation of the SEM

The most common method to analyse quantitative data is structural equation modelling (SEM) which consists of a group of techniques including confirmatory factor analysis (CFA) and path analysis. Despite the existing advantages of using SEM for the quantitative approach, some drawbacks and difficulties are including examining the large model in small samples, failing to compare the alternative concepts and models, lacking consideration of distribution assumptions before starting SEM, and applying insufficient methods for evaluating model fit (Goodboy & Kline, 2017).

Although under particular circumstances, the SEM approach tests the relationship between variables of interest in a given theoretical model (Raykov & Penev, 2001). Hence, one of the disadvantages of the SEM approach is comprehending the relation between the measurement model, its indicators, and latent variables to ensure the developed model or studied construct can be interpreted correctly.

Another major limitation of using SEM is the model verification feature applied in software such as SmartPLS because most software does not propose model validation. However, the selected software for this study as SmartPLS provided this opportunity for the explanatory factor analysis. In addition, the model validation aims to provide more evidence for the hypotheses and determine the construct or model from the collected data. While. In this study, the construct has been defined previously based on the preceding literature review. The CFA was performed to ensure whether the proposed model or construct is valid.

The generalisation of the outcome was the most important issue when the SEM was applied because outcomes from the SEM approaches are subjected to selection effects and sampling concerning at least three aspects, including individuals, measures, and occasions (Jeon, 2015).

To generalise the acquired results, it is required to conduct the cross-validation index. It means the computed results from a single sample should likely fit an independent sample. Then this model or index is useful to compare with alternative models.

Another limitation of the SEM approach is the nature of the latent variables. Because the nature of the LVs depends on how to define and select the indicators, which may influence results and interpretation (Jeon, 2015). Unfortunately, in this study, the transportation variable has been eliminated because the number of selected measures was insufficient. The third limitation of using the SEM approach is the occurrence of the measurement, as several potential parameters can affect the measurements afterwards. It means the time interval can affect the measurement; therefore, the collected data might not (or might) fit the developed construct during the time interval.

Although SEM is a useful approach to analyse multiple causes and effects between data, there are still several issues, such as the requirements of homogeneity and linearity of variances, the amount of the residual should not be correlated with variables that precede it in the model, the variable should measure on an interval scale, and the variable measure without any errors. Usually, it is complicated to collect data without any error; hence random or non-random errors can appear; nevertheless, they should not affect the validity of the measurement (Jeon, 2015). Most assumptions are hard to satisfy and therefore create a limitation for any study.

Several quality checks were considered to mitigate the above-mentioned issues to ensure the selected quantitative analysis is the best and most appropriate method for this study.

The normality tests were the first and most important quality checks applied after data collection. This study applied two normality tests, including Kolmogorov-Smirnov and Shapiro-Wilk tests, to ensure that the collected data does not follow normally distributed data. Hence, applying the non-parametric tests like a partial least square (PLS) approach is required to complete this study. In addition, descriptive analyses, including mean, skewness, and kurtosis, were applied to ensure the strength of the parameters. The quality criteria, including Cronbach's Alpha, total-item correlation, and Cronbach's Alpha if the item is deleted, were used to determine the internal consistency and reliability of the collected data. The enhanced literature review was preceded to ensure whether the developed sample size from the questionnaire was appropriate for the SEM analysis. It was concluded a minimum of 670

observations (10 observations per indicator) is required to conduct covariance-based SEM (CB/SEM) for the studied construct (Matthews et al. 2018). While in this study, 212 applicants replied to the survey successfully, which shows that the collected data and number of samples were not large enough to conduct the CB/SEM analysis. Hence, the PLS/SEM has been selected to examine the proposed construct and developed hypotheses.

3.11.4 Bootstrapping Approach

According to (Hesterberg 2011), the bootstrapping approach is a statistical method that resamples the obtained dataset to produce many simulated samples. This procedure allows researchers to compute the constructs' standard errors and confidence intervals and implement hypothesis testing for many types of sample statistics. The bootstrap approach is a more suitable alternative to traditional hypothesis testing and can be used for several conditions. In this study, after each round of CFA, the bootstrapping analysis was applied to testify the Tvalue (i.e., T-statistic) of the pathway between the indicator and variable and the pathway between variables. The bootstrapping approach is a nonparametric technique that tests the statistical significance of several PLS results such as R^2 value, path coefficient, Cronbach's Alpha, and Fornell-Larcker (Hair et al. 2017).

In this case, the T-value of the path coefficient should be higher than the absolute value of 1.96 (i.e., $|\pm 1.96|$) at 95% level of confidence. Any statistical significance between indicator variable shows whether the studied variables or items contribute to the model or not. In other words, the T-value of the pathway between indicator and variable higher than threshold limit $|\pm 1.96|$ at a significant value (@ P-value) higher than 0.05 was not contributed to the construct. Whereas if the T-value of the independent variable is higher than the accepted limit ($|\pm 1.96|$) at a significant value lower than 0.05, the variable will play an essential role in the prediction process (Gibson 2021).

3.12 Quality criteria

In addition, several criteria were considered to check the validity of the construct before and after omitting the items (i.e., indicators), including Composite Reliability (CR), Average Variance Extracted (AVE), Cronbach's Alpha, and discriminant validity based on Fornell-Larcker while conducting the CFA process.

Although Cronbach's Alpha is a common practice to test the reliability of the construct the test will be explained in detail in chapter 4, sections 4-8 (Bollen and Long 1993; Garson 2011; Cho and Kim 2015; Bae 2020; Mikhail et al. 2020). In addition, it is essential to check the quality of the construct using other statistical approaches, as explained in the following sections.

3.12.1 Cronbach's Alpha

The reliability and internal consistency of the collected data must be tested to ensure whether the accumulated data has been measured base on the considered criteria in the survey (Sharma et al. 2017). Hence, Cronbach's alpha index was assessed to examine the reliability of the scales. Fadaki et al. (2019a) recommend that if Cronbach's alpha scores are shown above 0.7 for scale robustness, the accumulated data would be reliable for further tests. Cronbach's alpha has been formulated as equation (1).

$$\alpha = \left(\frac{n}{n-1}\right) * \left(1 - \frac{\sum s_i^2}{s_t^2}\right) \qquad (1)$$

Where i is the number of the items, s_i^2 is the average covariance between item pairs, and s_t^2 presents the average variance. The SPSS software (IBM SPSS Statistics V.26) will be used to analyse the reliability and internal consistency.

3.12.2 Composite Reliability (CR)

The composite reliability (CR) was also considered reviewing the convergent validity of the construct at each round after removing the indicators from the construct. According to (Hair et al. 2011), the threshold limit of CR must be 0.7 and higher than it, which is calculated by equation 2.

$$CR = \frac{(\sum_{i=1}^{n} \lambda_{yi})^2}{(\sum_{i=1}^{n} \lambda_{yi})^2 + (\sum_{i=1}^{\rho} Var(\varepsilon_i))} \qquad (1)$$

Where CR indicates the composite reliability, λ_{yi} represents the standardised factor loading, and $Var\ (\varepsilon_i)$ shows the variance due to the measurement error.

3.12.3 Average Variance Extracted (AVE)

Another method to test the validity of the construct alongside the Cronbach's Alpha and CR was the average variance extracted (AVE). The AVE measures the level of variance captured by the proposed construct against the level error measurement. According to (Hair et al. 2011), the accepted limit of 0.5 and higher is an excellent level to show the validity of the construct. The applied CR in this study was calculated with Equation 3.

$$AVE = \frac{\sum_{i=1}^{n} {\lambda_i}^2}{n} \qquad (3)$$

Where AVE indicates the average variance extracted, λ_i represents the standardised factor loading, and n shows the number of items.

3.12.4 Discriminant Validity based on Fornell-Larcker criterion

Discriminant validity is applied to ensure no significant difference exists between the variance of different variables. The discriminant validity demonstrates the differences between one variable and another in the same construct, the standard approach to assessing the variance based construct in SEM (Shook et al. 2004; Shah and Goldstein 2006). In other words, the (Fornell and Larcker 1981) criterion was commonly applied to evaluate the degree of shared variance between the construct variables. It also calculates the differences between the overlapping models (Hair et al. 2017). In this study, the Fornell-Larcker criterion was applied after CFA and bootstrapping tests of the final round when the construct of drivers and moderators were approved. According to (Fornell and Larcker 1981), the correlation between each item and itself must be higher than the correlation between that items with other items. In addition, Hair et al. (2017) stated that a variable in a construct must describe the variance of its indicators better than the variance of other variables in the construct. Hence, the square root of AVE for each variable must have a greater value than the variance of other variables in the construct. Therefore, it is required to compare the square root of AVE for each variable placed on the diagonal of the matrix with the correlation coefficient for each construct in the relevant columns and rows or off the diagonal.

The main reason for applying discriminant validity based on the Fornell-Larcker criterion is its simplicity in calculating and comparing the results. According to Shiu et al. (2011) the Fornell-Larcker criterion can be applied more widely in various disciplines and is the most common approach to evaluating distinctiveness because it is required to conduct a single measurement to finalise the answer.

Several researchers have applied discriminant validity based on the Fornell-Larcker criterion for their study to demonstrate the correlation between each variable (Achenbach et al. 2005; Farrell and Rudd 2009; Henseler et al. 2015; Mohammadi and Mahmoodi 2019; Fadaki et al. 2020; Hilkenmeier et al. 2020). Hence, in this study, the discriminant validity is based on the

Fornell-Larcker criterion, which has been applied once to the final round of the driver's construct and another time for the final round of the moderator-driver's construct.

3.12.5 Analysis of R-squared (R^2)

R-squared value has also been named a coefficient of determination applied within the SEM analysis to determine how the proposed model fits the collected data in the concept of regression analysis. In PLS-SEM analysis, R^2 was applied for hypothesis testing; however, it is useful for predicting and forecasting approaches (Glantz et al. 1990; Draper and Smith 1998). To evaluate the precision of the estimation for the developed construct, it is required to examine the value of R^2 for the variables. Endogenous factors are variables that are affected by other variables in a construct. The R^2 parameter represents the blended or combined effect of the exogenous variables in the endogenous (Figueroa-García et al. 2018). In addition, R^2 is a squared value that consists of the fundamental and predicted correlation values. It also represents the variance in each endogenous model, which is explained by all other endogenous variables (Hair et al. 2011).

Falk and Miller (1992) stated that the calculated variance by R^2 for the endogenous model must be higher than 0.1. Moreover, the main aim of the calculation is to obtain a higher value of Rsquared because the PLS-SEM approach tends to maximise the amount of R^2 for the endogenous variable during the path analysis of a construct (Figueroa-García et al. 2018). Although the interpretation of the R^2 value depends on the nature of the research discipline, developed construct, and applied techniques with the SEM. It can be stated that an endogenous construct can be described as a substantial, moderate, and weak construct depending on the computed R^2 values if it is equal to and higher than 0.75, 0.50, or 0.25, respectively (Hair et al. 2017). Although the R-squared value must not be deemed merely to evaluate the fitness of the model but considering the R-squared value alongside the path coefficient and t-value can produce a reasonable prediction about the hypothesis model.

In this study, in chapter five (PLS-SEM section), the R-squared value has been computed and reported after each round of bootstrapping tests to verify the prediction or estimation of the developed hypothesis construct based on the collected data.

3.13 Interaction Effect between IV and DV

One of the novelties of this study is to propose three interaction effects as moderators, including Market, Basis & Foundation, and Business & Enterprise, between the SC drivers and DPP to see their effect on the TSCV variable. An interaction effect can be defined as a simultaneous effect between one dependent variable and two or more independent variables. It is essential to study the effect of the interaction parameters to identify how two or more independent variables act out together to affect the dependent variable (Lavrakas 2008).

The effect of moderators and mediators is essential in analysing complex correlations such as this study. Two indirect effects exist between IV and DV, including mediators and moderators. Figure 3-3 shows the simple moderator (Z) and mediator (W) between independent (IV) and dependent variables (DV) in a construct. A mediation effect (or mediator) defines a process through an extra variable that relates two variables. In contrast, the moderator or moderating effect explains the direction and strength of the relation between two variables (Baron and Kenny 1986).

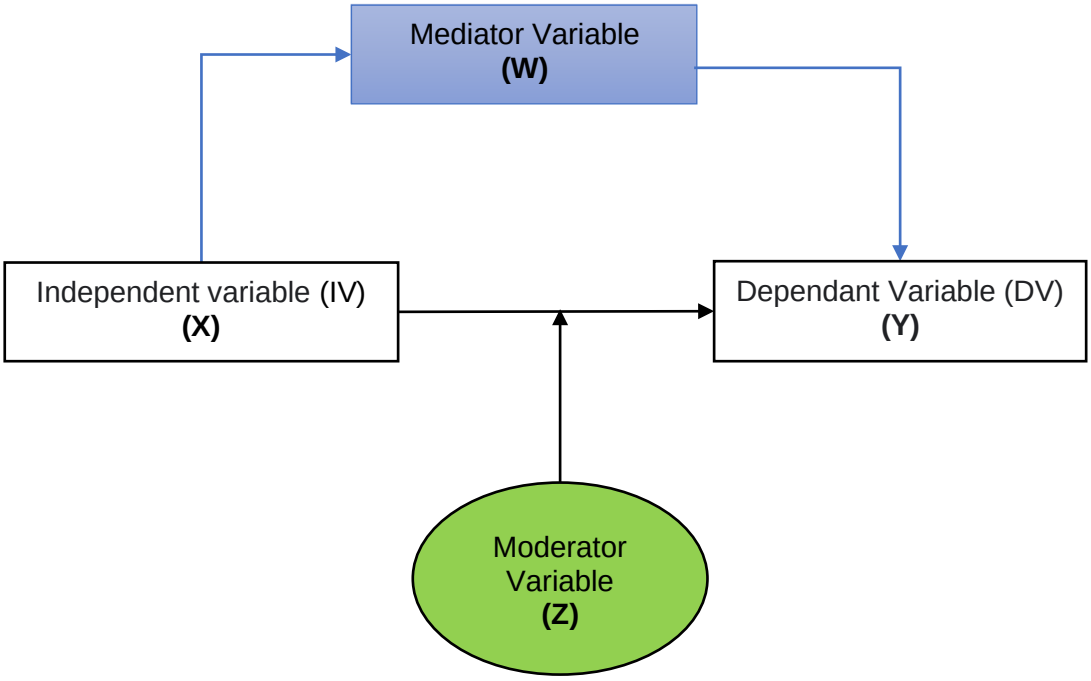


Figure 3-3- Schematic structure of moderation effect between independent and dependant variables.

Moderators can be classified into categorical and continuous, while DV can also be classified as categorical or continuous variables. In the categorical moderating effect, the nature of the moderator is dichotomous (i.e., it has two levels), such as male and female. In contrast, the

continuous variable has a socioeconomic effect that impacts some interventions between two variables through the main impact (Marsh et al. 2011).

In this study, the PLS and bootstrapping analyses have been conducted at the present of three continuous moderators using SmartPLS V3 software.

SmartPLS software provides various techniques to analyse the effect of interaction (as a moderator) between the variables, including two-stage (as a default), productivity, and orthogonalization. The productivity approach calculates all possible pairwise combinations between the moderator and variable. The two-stage approach uses the latent variable scores (LVs) of the moderator and predictor (independent variable) from the main model.

The LVs are applied and served to compute the product indicators of the second stage analysis, which contains the interaction terms of the moderator and predictor variables.

The orthogonalization approach applies residuals values computed by regressing all possible pairwise by multiplying the indicators of the predictor and moderator. The residual values are served as new indicators between the latent predictor and moderator as the interaction terms.

This technique will be orthogonal to all indicators (moderators and indicators) to ensure the indicators of the interaction term do not participate in any variance with any indicators of the moderator or predictor (Chin et al. 2003; Henseler and Chin 2010). The following example has been explored to show how the productivity approach created difficulties in reporting the possible outcomes of the interaction effect. For instance, the interaction effect between the supply chain drivers and Basis & Foundation (as a moderator) has been analysed using the productivity approach to test the third hypothesis. Because the approved indicators of supply chain drivers were fourteen and approved indicators of the Basis were four, the productivity approach will create 56 pairwise indicators (i.e., 14 * 4). The outcome of the PLS analysis showed 78-factor loadings for the indicators, including 56-factor loadings of an interaction effect, 14 outer loadings of supply drivers, four outer loadings of DPP, and four outer loadings Basis & Foundation as a moderator. In addition, another table for t-values with 78 rows should be considered as an outcome of conducting the bootstrapping analysis.

According to (Ramayah et al. 2018) two-stage approach can be applied to report the outcome of bootstrapping table (t-statistics) due to saving time of analysis and easiness of reporting the obtained results in this thesis. However, the path analysis report has incorporated the outcomes of two-stage and productivity approaches using the bootstrapping calculation to ensure the hypotheses have been analysed correctly.

Due to substantial calculation steps included within the productivity approach, it was decided to report all essential parts of calculations, including factor loadings, path coefficient (O), Tstatistics, etc. Therefore two-stage technique was applied for the main hypotheses (H3, H4, and H5) to report the path coefficient and T-values.

Furthermore, to demonstrate the consistency and quality of the study, for the main moderated hypotheses (H3, 4, and 5), the path analysis table has included the outcome of the two-stage approach and productivity technique. For all sub-hypotheses, moderators have applied the productivity approach to identify the interaction effect between the independent and dependent variables because fewer indicators are involved within the moderation effect.

3.14 Simple Slope Analysis (SSA)

A simple slope is defined as the regression of the dependant variable (DV as Y) on the independent variable or predictor (IV as X) in the presence of a moderator (Z).

The interaction effect can happen between two continuous variables, two dichotomous variables, or one continuous and a dichotomous variable.

For example, X is the independent variable, Y is the dependant variable, and Z is the moderator.

The regression equation can be formulated as follow

$$\hat{Y} = \hat{b}_0 + \hat{b}_1 X + \hat{b}_2 Z + \hat{b}_3 XZ \qquad (4)$$

Where, $\hat{Y}$ is the model implied value of Y, $\hat{b}_0$is the intercept of the equation, $\hat{b}_1, \hat{b}_2, and\ \hat{b}_3$ are the regression parameters, X is the first predicator, Z is the second predicator (moderator), XZ is the product between two predictors.

To highlight the regression of Y on X as a function of Z, Eq. 3 can be rearranged to give Eq. 4, including two parenthetical expressions, which the first term called simple intercept ($\hat{\omega}_0$) and the second term represents the simple slop ($\hat{\omega}_1$).

$$\hat{Y} = (\hat{b}_0 + \hat{b}_2 Z) + (\hat{b}_1 + \hat{b}_3 Z)X \qquad (5)$$

By replacing the values of $\hat{\omega}_0 = (\hat{b}_0 + \hat{b}_2 Z)$ and $\hat{\omega}_1 = (\hat{b}_1 + \hat{b}_3 Z)X$ in equation 4, the following equation can be rewritten.

$$\hat{Y} = \hat{\omega}_0 + \hat{\omega}_1 X \qquad (6)$$

To draw the simple slop graph, it is essential to find the values of $\hat{\omega}_0\ and\ \hat{\omega}_1$.

As discussed, if the interaction term ($\hat{b}_3$) was found significant at the assigned alpha-level, the regression of Y on X can be analysed and drawn to understand the nature of the interaction effect.

In other words, following finding the significant interaction effect between two variables of (X) and (Y) in the presence of Z as moderator, it is recommended to determine the nature of the interaction using the simple slope test method (Dawson and Richter 2006; Dawson 2014). Figure 3-4 (a) and (b) show no interaction effect between IV and DV in the presence of the moderator (Z). Z_1 and Z_2 can be any measure like male and female, which shows that the moderator is categorised as a gender. The difference between Z_1 and Z_2 is constant in both graphs, proving that the moderator (difference between the genders) does not vary by the difference of X level from low to high values.

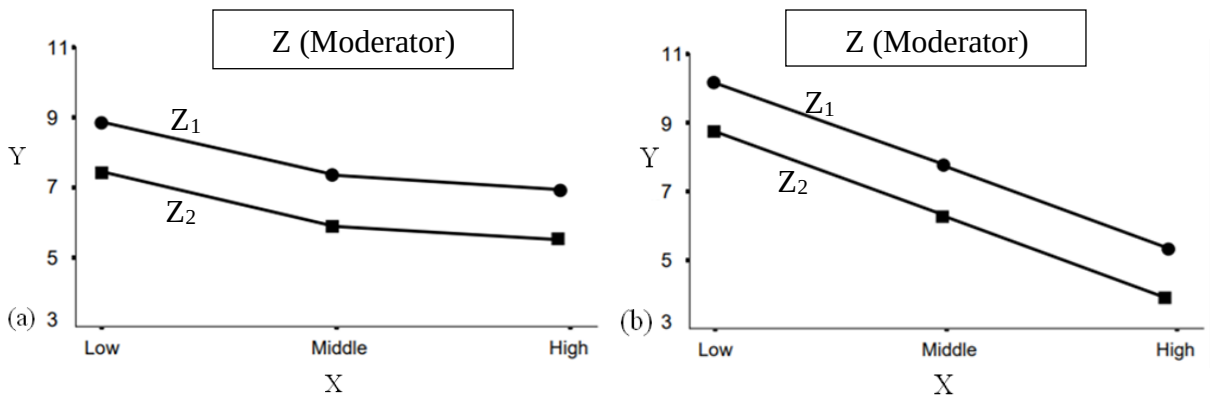


Figure 3-4 (a) and (b): There is no interaction effect has occurred between two variables (X and Y) in the presence of moderator Z.

Whether the slope of the regression lines between two variables in the presence of a moderator can be positive or negative, the interaction effect can happen in two ways, including ordinal or disordinal interaction. Figure 3-5 shows the ordinal and disordinal interaction effects between IV and DV in the presence of a moderator (Z).

For the ordinal interaction effect, the interaction coefficient ($\hat{b}_3$) in Eq.5 is a slight negative or positive value, and the cross-over point (C) does not appear between the upper and lower limits of IV or DV; therefore, it would be difficult to estimate it. In other words, the slope of the lines might be tended to the positive or negative infinity ($\pm\infty$) and hardly converge at a point between the maximum and minimum of the IV and/or DV within the graph (Widaman et al. 2012). A disordinal interaction includes a cross-over value within the observed range of values.

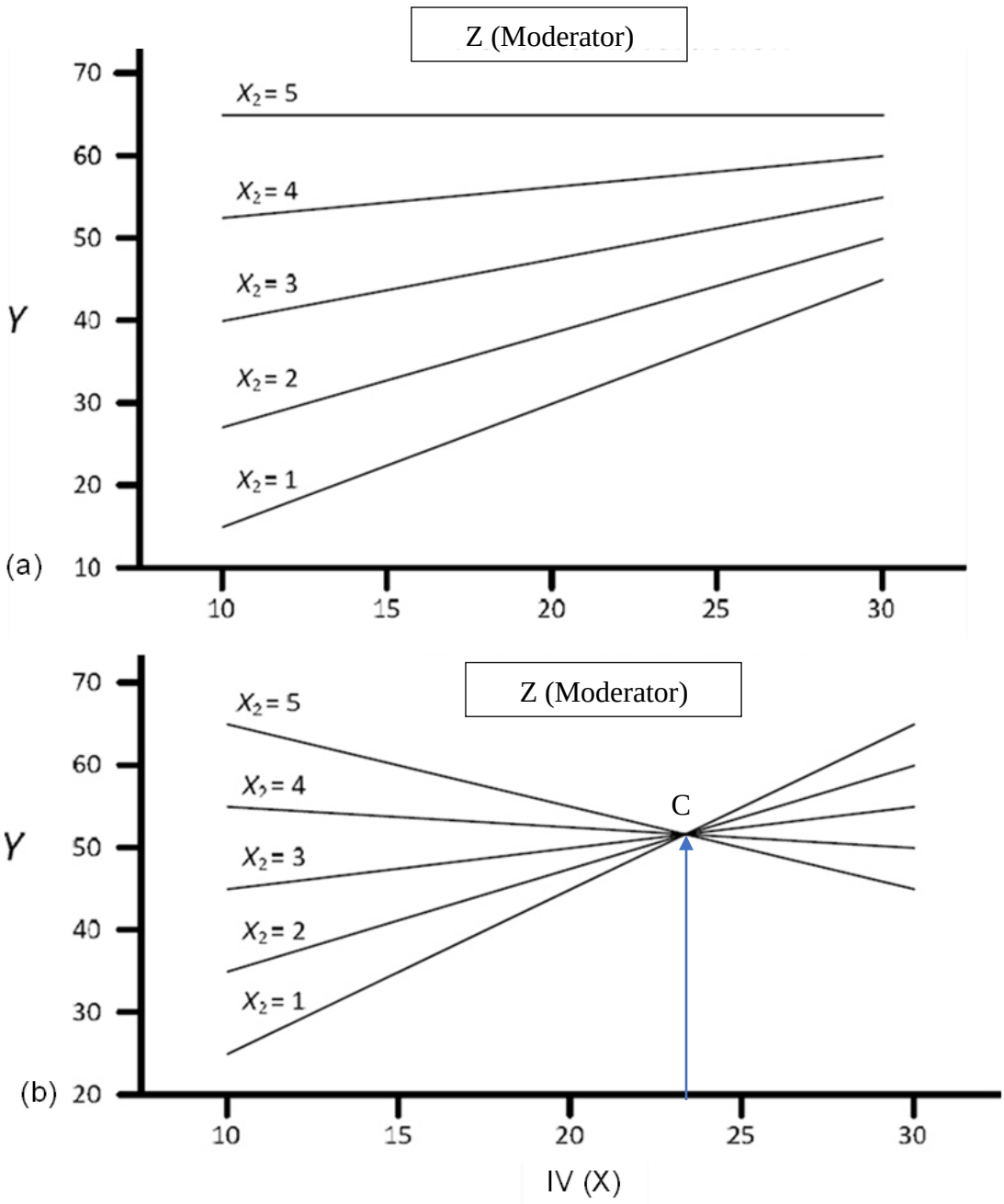


Figure 3-5 (a) and (b): There is no interaction effect has occurred between two variables (X and Y) in the presence of moderator Z.

Hence, the simple slope test was carried out after bootstrapping analysis for the main hypotheses (i.e., H3, H4, and H5) to determine whether a significant interaction positively affects the dependent variable or negative.

Dawson (2014) suggested that the interaction approach should complete by drawing the interaction plot between variables to realise the direction of the moderation effect if the interaction effect is significant. Plotting the moderation effect between two variables' outcomes

helps to understand the interaction effect between them and whether it has a positive or negative impact on a dependent variable. For example, suppose there is a significant interaction between supply chain drivers (X, independent variable) and basis & foundation (Z, moderator variable) to predict the position of DPP (Y, dependent variable). In that case, this effect can be interpreted in two different ways. It might be that the supply chain drivers likely change the position of DPP towards agility in the presence of a higher effect of basis and foundation (a dominance hypothesis). Conversely, in the interaction effect of basis and foundation, the combination between the moderator and supply chain drivers might change the position of DPP from agility to lean principle. Hence, drawing the interaction effect using a simple slop test is necessary to interpret how the moderator changes the stream between IV and DV.

3.15 Testing the total variance of the variables

To ensure various SCs' indicators (i.e., measures) can be merged into one driver (i.e., factor), the exploratory factor analysis using SPSS software (IBM SPSS Statistics V.26) was conducted between cumulative and separate measures to check the Uni-dimensionality of both conditions.

Table 3-14 shows the total variance of the selected indicators divided between several factors and merged into one. The accepted factors and measures were appropriately loaded to the proposed construct to evaluate the model's validity and internal reliability between the two conditions. It has been demonstrated that extracted variance (77.30%) between two conditions was highly coordinated, thereby confirming that all indicators can be combined in one supply chain driver

Table 3-14-Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% Of Variance	Cumulative %	Total	% Of Variance	Cumulative %
1	12.367	77.297	77.297	12.367	77.297	77.297
2	0.711	4.442	81.739			
3	0.473	2.959	84.698			
4	0.438	2.740	87.438			
5	0.396	2.476	89.914			
6	0.305	1.905	91.818			

7	0.261	1.633	93.451			
8	0.218	1.361	94.813			
9	0.194	1.212	96.025			
10	0.191	1.192	97.217			
11	0.133	0.829	98.047			
12	0.112	0.698	98.745			
13	0.087	0.545	99.290			
14	0.052	0.325	99.615			
15	0.038	0.238	99.853			
16	0.024	0.147	100.000			
Extraction Method: Principal Component Analysis.						

3.16 Challenges of Data Collection

The high volume of data is one of the most challenging issues researchers face. More than 16188 singular data were collected for 76 indicators from 212 applicants in this research study. There are some common issues and biases when the data is collected. Selecting the right analytical tool and method depends on the volume of collected data, data visualisation, various sources of data collection, low-quality data, collecting meaningful data, data security, and inaccessibility (Fan et al. 2014).

For instance, selecting an appropriate analytical tool is a significant challenge in this study. There are typically two methods to measure the parameters of SEM named variance-based (i.e., component-based) and the covariance-based approach (CB/SEM) (Haenlein and Kaplan 2004). While in this study, 212 applicants responded to the survey successfully, showing that the collected data and number of samples are insufficient to conduct the CB/SEM analysis (Matthews et al. 2018). Hence, the PLS/SEM has been selected to analyse the proposed construct for this study.

One of the significant issues in data analysis and quantitative study is managing and storing data, including but not limited to data collection, creating reports, and influencing further analyses. Updating manual data sheets also creates more errors and inaccuracies. Hence, the automated tool (i.e., Excel) was considered to collect and save data accurately. Also, the applied software helped to make initial descriptive data analyses to identify any discrepancies or odd values and collect data gain, if necessary, to ensure the accumulated data has less error and bias.

In this research, data scaling was considered another major issue. At the beginning of the study, it has been attempted to manage the volume of data and distinguish between accurate and inaccurate data. Also, it was imperative to consider how many SC drivers must study for this thesis because collecting meaningful and scaling data affected the adopted analytical approach and even the selected software. On the other hand, data engineering must be avoided during the collected data. Hence, the preceding literature review has been conducted accurately to ensure all the variables (SC drivers, DPP, and TSCV variables) are selected appropriately. Also, before conducting the survey, the developed questionary was reviewed two times by seven SC experts to improve the quality and validity of the questionnaire. It was ensured that the purpose of the questions was clear to the participants. During the interview with experts, the main goals of the research, the findings from the literature, the proposed hypothesis, and the developed constructs were explained to the experts. The conducted interviews mitigated the major challenges and improved the reliability and validity of the questionary.

Another major challenge of this study was data security and setting up security measures to minimise the risk of leaking data for the persons who were not involved in this study (Kuner et al., 2012). According to ethical approval, all information provided by the participants must be treated with total confidentiality. Thereby, to avoid any possible data leaking, some mitigation procedures were considered, including encrypting data with secured login credentials, completing essential training on the security of big data, and controlling access rights to eligible persons.

Another obstacle to completing the success of data analysis depends on the company culture. Most companies claimed that frames' culture was the biggest obstacle to collecting accurate data because most companies are not data-driven or have no experts to analyse the data. To mitigate this issue, it has been attempted to select companies with data analysers and trained employees to support data culture (Díaz et al., 2018).

Common method bias in variance-based technique (i.e., PLS/SEM) is a phenomenon created by the measurement method applied in the SEM approach, not the network of the causes and effects in the proposed construct. For instance, any instruction at the top of the survey and questionnaire might influence the answers collected by diverse applicants in a similar general trend and create a certain amount of expected variation. The implicit social desirability can be another possible source of common method bias during the collection of the answer using a survey. If the applicants have the same attraction to certain applied methods in their companies or other firms, they might answer the questions with a certain amount of common variation

(Kock, 2015). In this study, the results with common and without common bias have been compared randomly using SmartPLS to see how many discrepancies existed for a certain path analysis and hypothesis. The random examination of the results with and without common bias certified that the common bias has not affected the acquired results of this study significantly.

For considering the element of endogeneity, the hypotheses developed through the literature review and the causal relationship between endogenous and exogenous variables as shown in the conceptual model were well grounded in the literature. The reverse relationship between independent and dependent variables if at all exists, (i.e., endogeneity) was not supported in the literature. Hence, the effect of endogeneity was outside of the scope of this research and therefore was not examined.

3.17 Concluded Remarks

In this chapter, the entire research methodology has been reviewed and discussed to determine the best method to conduct this study and achieve the aims and objectives of the thesis. It has been concluded that the selected research method is based on a deductive approach to observe whether the proposed hypotheses were confirmed by collecting data from the participants.

Methodological suitability is defined as the dataset's appropriateness and fitness to the study's intended goal; particularly, it is extended to how the collected data can satisfy the research aims and objectives (Shang et al., 2018). Several research methods can generally be selected for any research study.

The research onion methodology was applied in this study to explain all possible options and select the best-fitted method for this study. The possible choices in research methodologies and alternative options were explained for each section (Sections 3-2, 3-3, 3-4, and 3-5). In addition, the reasons for the chosen approach for this research have been explained; accordingly, this includes the nature of the study, preceding literature review, type of accumulated data, developed hypotheses, method of collecting data, and knowledge gap, which were used to select the specified research approach for this study.

Regarding the nature of this study, the number of experts, and considering the COVID-19 situation, the questionnaire survey has been selected to collect the data from the companies and participants. Before conducting any data collection, the ethical approval form was obtained from Bournemouth University. The reliability and validity of the questionnaire survey were checked by asking seven experts in this field before the data collection was started. This step

was crucial for this study to ensure that the questions conveyed the correct message to the participants and that questions appropriately reflected the aims of the hypotheses.

Two well-known strategies in the SC literature are lean and agile. The effect of the lean-agile, otherwise known as 'leagile' and its impact on the improvement and growth of the furniture, agricultural machinery and equipment, and trout fish in SC management studies has been neglected. For this study, the deductive approach was utilised to evaluate the effect of the Leagile factors on the furniture, agricultural machinery and equipment, and trout fish supply chain, answer the research questions, and assess the proposed hypothesis.

Scholars emphasised identifying the best practice of implementing the leagile supply chain strategy in various SC that affects the supply chain drivers and performance (Goldsby et al. 2006b; Naim and Gosling 2011). To address the research gap, this study intends to examine the relationships between the LSCS factor (DPP), supply chain drivers (distribution, production, inventory, information, and location), and supply chain performance (in terms of TSCV including cost, lead-time, service, and quality). This chapter focuses on the research methodology's outlines and steps.

Empirical inconsistencies in the literature relating to the implementation of LSCS practices and the effect on SC's drivers and supply chain performance demonstrate the complexity of the supply chain strategic management. Most of the reviewed literature advises that considering LSCS is beneficial; however, the performance of the SC after implementing the LSCS upon different SC drivers was varied among studies (Li et al. 2019). Although, the explained LSCS has a level of complexity and inconsistency, which may be challenging to apply to the supply chain. Nevertheless, this study aims to develop a systematic and quantitative framework for the furniture, agricultural machinery and equipment, and trout fish supply chain practitioners in the north of Iran. Indeed, testing the proposed construct's validity may help define logical and practical LSCS implementation (Rahiminezhad Galankashi and Helmi 2016a). An experimental design could be a quantitative option for this research. In this manner, the independent variables could be controlled and whether the independent variables certainly affect the dependent variable could be evaluated (Gunasekaran et al. 2017).

The main factors of leagile supply chain strategy, SCs' drivers, and performance metrics of the SC have been explored by reviewing the literature. Moreover, the interrelation between LSCS factors, SC drivers, and SC performance metrics was identified by reviewing the literature.

Hence, four main hypotheses were developed and explained in chapter 3; however, two constructs have been considered for testing the validity of the hypotheses. The constructs are

examined by the developed hypotheses based on analysing the impact of LSCV factors on the SCs' drivers on the TSCV.

Four steps are defined for the survey, including collecting the companies' and participants' information, developing a questionnaire form, validating the questionnaire form using interviews, and sending the form to the selected SC. After collecting the questionnaire, the reliability and internal consistency of the data would be tested by Cronbach's alpha. The Confirmatory Factor Analysis (CFA) method will be applied to test the validity of the proposed constructs

By considering the nature of the collected data and completing the obtained results of the normality test in chapter 4, The CFA and SEM analyses were considered to reduce the number of the factors and variables as well as validate the hypotheses by checking the path analysis Figure 3-6 illustrates a diagram of the deductive approach for the research study. After conducting path analysis, the supported hypotheses and sub-hypotheses remained in the construct, acknowledging that the proposed construct has been partially approved. The implication of validated hypotheses on the construct, SC, and associated companies have been discussed, and lastly, the validated construct was presented in the conclusion chapter.

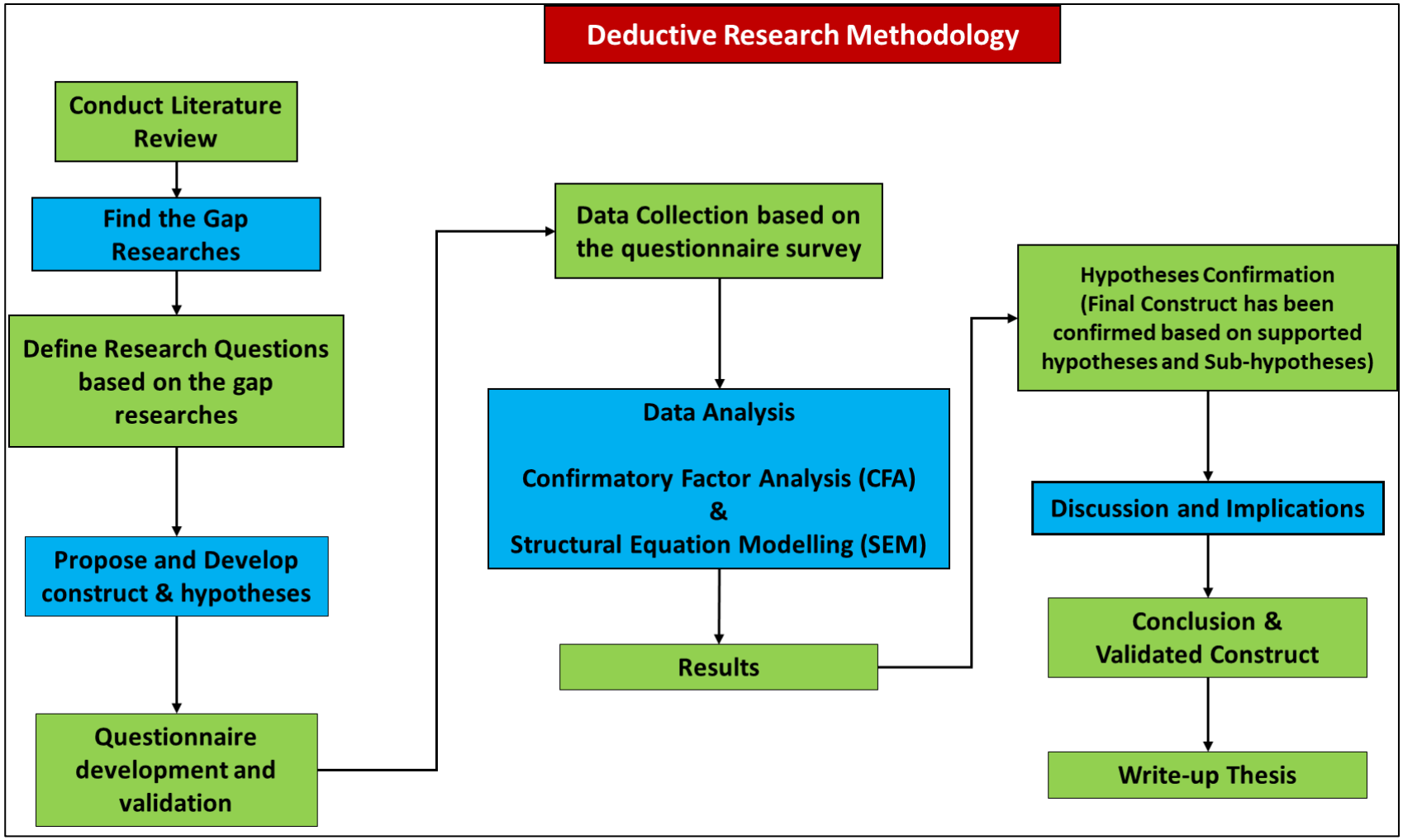


Figure 3-6- The deductive research methodology was deployed for this study.

Chapter 4 Basic Data Analyses and Descriptive Tests

4.1 Introduction

In this chapter, the primary data analysis and initial statistical tests were conducted to evaluate whether the collected data showed enough reliability and validity to proceed in the next chapter. This chapter uses Microsoft Excel (V.2016) to record data and import them to SPSS (IBM SPSS Statistics V.26) software. Demographic analysis of collected data has been conducted to determine all the aspects and details of the collected data, including the name of industrial clusters, participants' educational background, experience at work, etc.

The normality test is essential for the continuous data to decide what statistical methods should be selected for data analysis and measure central tendency (Mishra et al. 2019a). In this chapter, the normality test of the collected data was examined using two different methods, including the Kolmogorov-Smirnov test and the Shapiro-Wilk test.

Descriptive statistics show the basic information about the variables in the data set and quantitatively describe the potential relationship between variables. The descriptive analysis provides a basic structure of collected data and demonstrates the preliminary outlines of the samples and measures (Bhattacherjee 2012). This chapter analysed the minimum, maximum, mean, standard deviation, skewness, and kurtosis of all variables using SPSS software (IBM SPSS Statistics V.26). The effect of each variable and its measures on the other variables are violated to demonstrate the validity of the nature of collected data for each variable separately. Furthermore, the reliability and internal consistency of collected data were assessed using Cronbach's alpha without considering the interaction between the variables. Also, the inter item correlation between measurers of each variable has been separately evaluated to determine whether they were correlated to each other to measure variable consistency. After each inter-item correlation analysis, the collected data and accumulated answers were doubled check to ensure the validity and reliability of the collected data (as well as the validity of questions and questionnaire survey) were not violated.

4.2 Response Rate

To collect data, first, a list of companies within three industrial clusters have been gathered. Then, we ask companies to introduce an eligible person who has enough experience in the company, working in the position that is relevant to SC, collaborating with other companies within their industrial cluster, and have minimum knowledge of the company's business as usual. In this way, a list of 281 respondents was collected. After the initial evaluation, 254

eligible were selected for participating in the survey. Finally, 43 participants have been removed from the survey due to the panel selection questions and fail to return the response in time. Table 4-1 presents the number and percentages of the participants according to the industrial cluster, work experience within the industrial cluster, job title, education, size in terms of the number of employee education, and the number of years that the company joined the industrial cluster

4.3 Data Processing and Analysis

Samples were collected and entered into a worksheet in Microsoft Excel. Then the datasheet was reviewed, and the blank cell and wrong data were removed. The collected data has been imported to SPSS (IBM SPSS Statistics V.26) from Excel Spreadsheet (Microsoft Excel V.2016).

4.4 Demographic analysis of collected Data

First, a list of companies within three industrial clusters has been gathered to collect data. Then, we ask companies to introduce an eligible person with enough experience in the company, working in the position relevant to SC, and collaborating with other companies within their industrial cluster. In this way, a list of 281 respondents was collected. After the initial evaluation, 254 eligible participants were selected for the survey. Finally, 42 participants were removed from the survey due to the panel selection questions and failed to return their responses in time. Table 4-1 presents the number and percentages of the participants according to the industrial cluster, work experience within the industrial cluster, job title, education, size in terms of employee's education, and the number of years that the company joined the industrial cluster. In addition, 20% of the respondents had less than five years of experience, 76% had work experience between 5 to 20 years, and 4% had experience working in industrial clusters for more than 20 years. Thus, it can be confirmed that most participants in this study had at least 5 to 20 years of experience in both SC strategies and industrial cluster design. 56% and 32% of the companies that participated in this study were small and medium-size, and about 12% of large companies.

This result was expected given the nature of industrial clusters (Claver-Cortés et al. 2020), consisting of small and medium units.

Table 4-1- Demographic analysis of collected data.					
	n	%		n	%
Industrial clusters			**Work experience within an industrial cluster**		
Wood and furniture products	98	46	<5 Years	43	20

Agricultural machinery and equipment	71	33	5–9 Years	67	32
Food and fish	43	20	10–20 Years	94	44
			>20 Years	8	4
Work experience			**Industry sector**		
<5 Years	23	11	Food product	36	17
5–9 Years	73	34	Wood and fibreboard	73	34
10–20 Years	81	37	Metal	13	6
>20 Years	35	17	Textile	15	7
Respondent job title			Chemical	4	2
Managing Director	24	11	Machinery, and equipment	59	28
SC manager	33	16	Retail	10	5
Operation manager	30	14	Other	2	1
Procurement/Purchasing Manager	27	13	**Education**		
Inventory manager	31	15	Bachelor and below	88	42
Retail and Marketing Managers	33	16	Master	101	48
Distribution manager	26	12	PhD & above	23	11
Other	8	4	**Years Since the company joined the industrial cluster**		
Number of employees					
<30	119	56			
30-60	64	32	<3 years	12	5
60-100	21	9	3-8 years	44	21
>100	8	3	>8years	156	74

4.5 Descriptive Data Analysis

A descriptive statistic is a practical approach to show the basic information about the variables in the data set and quantitatively describe the potential relationship between variables. The descriptive analysis provides a basic structure of collected data and demonstrates the preliminary outlines of the samples and measures (Bhattacherjee 2012). Hence it is necessary to carry out the descriptive data analysis before the primary analyses.

This section summarises the minimum, maximum, mean, standard deviation, skewness, and kurtosis of all variables using SPSS software (IBM SPSS Statistics V.26). The considered variables are included five supply chain (SC) drivers, decoupling point position (DPP), total supply chain value (TSCV), and three moderators, which are analysed separately. Five SC drivers consisted of production, location, inventory, information, and transportation, while three moderators included basis & foundation, market, and business & enterprise.

The mean of each measure (or variable) shows how most participants have selected their values from the Likert scale. Depending on the participant's choice, the average of each measure or variable can be upper or lower than the midpoint of the Likert scale, which may be interpreted initially based on a type of variable. The standard deviation measures how the accumulated data has been distributed from the mean. The calculated standard deviation is higher if the collected data is spread out.

The kurtosis and skewness analyses examine whether the collected data meet normality assumptions. The kurtosis measures the normality of the curve by comparing the tails of distribution with the tails of a normal distribution curve. The data set with long tails or outliners have a high kurtosis, whereas the data set with low kurtosis have shown short tails or fewer outliners (Kline 2005).

The skewness also quantifies an asymmetry or distortion of collected data from the normal distribution. A positive or negative skewness refers to the sample curve, which is shifted to the left or right from a normal distribution curve. For kurtosis and skewness, the acceptable range (i.e., the lower and upper values) to show a normal distribution is considered between -2 and +2 (George 2011). If the values of asymmetry and kurtosis are near zero, the collected data is very standard; however, statistical analysis should be conducted to ensure the normality assumption of the data set is not violated.

4.5.1 Descriptive analysis of production driver

Five drivers were considered to evaluate supply chain drivers' effect on DP's position. The production driver was one of the SC drivers. Seven different measures were identified to measure the impact of the production driver on the DPP. Therefore, seven questions have been included in the questionnaire to address their variables accordingly. Table 4-2 shows the production driver's descriptive analysis, including mean, standard deviation, kurtosis, and skewness.

The mean value of all measures of the production driver is higher than the midpoint of the Likert scale, which indicates that the production driver might influence the position of DP significantly for the selected companies and their participants. However, the fluctuating mean values (upper and lower of the midpoint) indicate that further statistical analysis is required to determine the effect of the driver on DPP. The standard deviation values show that a range of collected data is covered by approximately 1.5 standard deviations above and 1.5 standard deviations below the mean, including 68% to 95% of observation. In addition, the Kurtosis

and Skewness of all production variables were within the range of -2 to +2. Hence, it might be considered a normal distribution for the measures; however, it is necessary to conduct a normality test to ensure the normality assumption is not violated.

Table 4-2-Descriptive statistics of production deriver.

	No	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
Pro1	212	1	5	3	1.413	-0.012	-1.264
Pro2	212	0	5	3.23	1.362	-0.358	-1.011
Pro3	212	0	5	2.82	1.430	0.123	-1.333
Pro4	212	1	5	3.07	1.414	-0.035	-1.292
Pro5	212	0	5	2.79	1.355	0.173	-1.071
Pro6	212	1	5	2.94	1.435	0.06	-1.313
Pro7	212	1	5	3.01	1.421	-0.037	-1.298

4.5.2 Descriptive analysis of inventory driver

The inventory driver was one of the SC drivers to examine its effect on the DPP and TSCV. Six different measures were identified to measure the effect of inventory driver on the DPP; thus, six questions have been included in the questionnaire to address their variables accordingly. Table 4-3 shows the inventory driver's descriptive analysis, including mean, standard deviation, kurtosis, and skewness. Participants have considered the maximum and minimum values of the Likert scale for all measures of this variable.

In addition, the mean value of all measures of this driver is higher than the midpoint of the Likert scale, indicating that the inventory driver might significantly influence the position of DP for the selected companies and their participants. However, the fluctuating mean values (upper and lower midpoint) indicate that further statistical analysis is required to determine the effect of the driver on DPP. The standard deviation values show that a range of collected data is covered by approximately 1.5 standard deviations above and 1.5 standard deviations below the mean, including 68% to 95% of observation. In addition, the Kurtosis and Skewness of all inventory variables were within the range of -2 to +2. Hence, it might be considered a normal distribution for the measures; however, it is necessary to conduct a normality analysis to ensure the normality assumption is not violated.

Table 4-3- Descriptive statistics of inventory driver.							
	No	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
Inv1	212	0	5	3.10	1.410	-0.094	-1.212
Inv2	212	1	5	3.01	1.451	-0.045	-1.324
Inv3	212	0	5	2.87	1.408	0.083	-1.217
Inv4	212	1	5	2.83	1.401	0.202	-1.194
Inv5	212	1	5	3.03	1.399	-0.017	-1.234
Inv6	212	1	5	2.92	1.383	0.102	-1.221

4.5.3 Descriptive analysis of location driver

The location driver was one of the SC drivers to examine its effect on the DPP and TSCV. To measure the effect of location driver on the DPP, four different measures were identified, and therefore, four questions have been included in the questionnaire to address their variables accordingly. Table 4-4 shows the location driver's descriptive analysis, including mean, standard deviation, kurtosis, and skewness. Participants have considered the maximum and minimum values of the Likert scale for all measures of this variable.

In addition, the mean value of all measures of this driver is higher than the midpoint of the Likert scale, indicating that the location driver might influence the position of DP considerably for the selected companies and their participants. However, the fluctuating mean values (upper and lower midpoint) indicate that further statistical analysis is required to determine the effect of the driver on DPP. The standard deviation values show that a range of collected data is covered by approximately 1.5 standard deviations above and 1.5 standard deviations below the mean, including 68% to 95% of observation. In addition, the Kurtosis and Skewness of all location variables were within the range of -2 to +2. Hence, it might be considered a normal distribution for the measures; however, it is necessary to conduct statistical analysis to ensure the normality assumption is not violated.

Table 4-4- Descriptive statistics of location driver							
	No	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
Loc1	212	1	5	2.95	1.401	0.01	-1.252
Loc2	212	0	5	3.11	1.422	-0.053	-1.233
Loc3	212	0	5	3.08	1.445	-0.152	-1.273
Loc4	212	1	5	2.93	1.434	0.067	-1.298
Loc5	212	1	5	3.07	1.426	-0.068	-1.306

4.5.4 Descriptive analysis of information driver

The information driver was one of the SC drivers to examine its effect on the DPP and TSCV. To measure the effect of information driver on the DPP, nine different measures were identified, and therefore nine questions have been included in the questionnaire to address their variables accordingly. Table 4-5 shows the information driver's descriptive analysis, including mean, standard deviation, kurtosis, and skewness. Participants have considered the maximum and minimum values of the Likert scale for all measures of this variable. In addition, the mean value of all measures of this driver is higher than the midpoint of the Likert scale, which indicates that the information driver might influence the position of DP considerably for the selected companies and their participants. However, the fluctuating mean values (upper and lower midpoint) indicate that further statistical analysis is required to determine the effect of the driver on DPP. The standard deviation values show that a range of collected data is covered by approximately 1.5 standard deviations above and 1.5 standard deviations below the mean, including 68% to 95% of observation. In addition, the Kurtosis and Skewness of all information variables were within the range of -2 to +2. Hence, it might be considered a normal distribution for the measures. However, it is necessary to conduct statistical analysis to ensure the normality assumption is not violated.

Table 4-5- Descriptive statistics of information driver.							
	No	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
Inf1	212	1	5	2.99	1.446	-0.042	-1.334
Inf2	212	0	5	3.08	1.405	-0.100	-1.181
Inf3	212	1	5	2.97	1.458	0.002	-1.346
Inf4	212	0	5	3.02	1.457	0.023	-1.340
Inf5	212	0	5	3.09	1.398	-0.022	-1.247
Inf6	212	0	5	2.87	1.393	0.018	-1.218
Inf7	212	1	5	2.92	1.392	0.04	-1.226
Inf8	212	1	5	3	1.436	-0.001	-1.291
Inf9	212	1	5	3.10	1.407	-0.062	-1.252

4.5.5 Descriptive analysis of transportation driver

The transportation driver was the last factor of SC drivers, which has been considered to examine its effect on the DPP and TSCV. To measure the effect of transportation driver on the DPP, three different measures were identified whereby three questions have been included in the questionnaire to address their variables accordingly. Table 4-6 shows the transportation driver's descriptive analysis, including mean, standard deviation, kurtosis, and skewness.

Participants have considered the maximum and minimum values of the Likert scale for all measures of this variable.

Also, the mean value of all measures of this driver is slightly higher than the midpoint of the Likert scale, indicating that the transportation driver might affect the position of DP for the selected companies and their participants. However, the fluctuating mean values (upper and lower midpoint) indicate that further statistical analysis is required to determine the effect of the driver on DPP. The standard deviation values show that a range of collected data is covered by approximately 1.5 standard deviations above and 1.5 standard deviations below the mean, including 68% to 95% of observation. In addition, the Kurtosis and Skewness of all transportation variables were within the range of -2 to +2. Hence, it might be considered a normal distribution for the measures. However, it is necessary to conduct a normality analysis to ensure the normality assumption is not violated.

Table 4-6- Descriptive statistics of transportation driver.							
	No	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
Tran1	212	0	5	2.95	1.453	0.027	-1.272
Tran2	212	0	5	2.94	1.404	-0.035	-1.245
Tran3	212	0	5	3.09	1.431	-0.138	-1.231

4.5.6 Descriptive analysis of the DPP

The decoupling point's position has been considered a major variable to identify the propensity of adopted strategy for the selected industrial clusters. In fact, with the help of DPP, it can be understood what type of strategy (from lean to the agile side) has been integrated into the companies of industrial clusters. Although the SC drivers have affected the DPP variable, the DPP also affects the TSCV factor. Hence, the DPP variable has been considered as an independent variable to examine its effect on the TSCV as a dependent variable. To measure the effect of DPP driver on the TSCV, eight different measures were identified whereby eight questions have been included in the questionnaire to address their variables accordingly. Table 4-7 shows the descriptive analysis of the DPP driver, including mean, standard deviation, kurtosis, and skewness. Participants have considered the maximum and minimum values of the Likert scale for all measures of this variable.

In addition, the mean value of all measures of this driver is higher than the midpoint of the Likert scale, which indicates that the DPP driver might influence the TSCV considerably for the selected companies and their participants. However, the fluctuating mean values (upper and lower midpoint) demonstrated that further statistical analysis is required to determine the effect of DPP on TSCV.

The standard deviation values show that a range of collected data is covered by approximately 1.5 standard deviations above and 1.5 standard deviations below the mean, including 68% to 95% of observation. In addition, the Kurtosis and Skewness of all DPP variables were within the range of -2 to +2. Hence, it might be considered a normal distribution for the measures; however, it is necessary to conduct a normality analysis to ensure the normality assumption is not violated.

Table 4-7- Descriptive statistics of decoupling point position (DPP).							
	No	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
DPP1	212	0	5	3.08	1.333	-0.115	-1.157
DPP2	212	0	5	3.00	1.470	0.018	-1.339
DPP3	212	0	5	2.98	1.462	-0.005	-1.320
DPP4	212	1	5	3.10	1.373	0.022	-1.235
DPP5	212	0	5	2.98	1.447	0.033	-1.271
DPP6	212	0	5	3.22	1.442	-0.260	-1.193
DPP7	212	0	5	2.94	1.464	0.034	-1.319
DPP8	212	0	5	2.95	1.393	0.042	-1.178

4.5.7 Descriptive analysis of TSCV

Five factors of supply chain drivers could change DPP, while DPP itself might affect TSCV. On the other hand, as per customer perception, the TSCV has been influenced by the quality, cost, lead time, and service (Johansson et al. 1993).

To measure how the quality, cost, lead-time, and service affected TSCV, four different measures were identified. Four questions were included in the questionnaire to address their variables accordingly. Table 4-8 shows the descriptive analysis of the TSCV variable, including mean, standard deviation, kurtosis, and skewness. Participants have considered the maximum and minimum values of the Likert scale for all measures of this variable.

In addition, the mean value of all measures of this driver is higher than the midpoint of the Likert scale (2.5). However, the fluctuating mean values of all measures indicate that further statistical analysis is required to examine the effect of its measures on TSCV.

The standard deviation values show that a range of collected data is covered by approximately 1.5 standard deviations above and 1.5 standard deviations below the mean, including 68% to 95% of observation. In addition, the Kurtosis and Skewness of all TSCVs indicators were within the range of -2 to +2.

Hence, it might be considered a normal distribution for the measures; however, it is necessary to conduct statistical analysis to ensure the normality assumption is not violated.

Table 4-8- Descriptive statistics of total supply chain value (TSCV)							
	No	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
Tscv1	212	0	5	3.07	1.424	-0.086	-1.195
Tscv2	212	0	5	2.88	1.436	0.111	-1.238
Tscv3	212	0	5	2.95	1.261	0.047	-0.939
Tscv4	212	0	5	2.96	1.270	0.014	-0.884

4.5.8 Descriptive analysis of basis & foundation

Three moderators, including market, basis & foundation, and business & enterprise, have been considered between the SC drivers and DPP to study the moderation effect. To measure the effect of basis & foundation between SC drivers and DPP, ten different measures were identified. Ten questions were included in the questionnaire to address their variables accordingly. Table 4-9 shows the descriptive analysis of the basis & foundation variable as moderators, including mean, standard deviation, kurtosis, and skewness. Participants have considered the maximum and minimum values of the Likert scale for all measures of this variable.

Furthermore, the mean value of Bas 4, 8, 9, and 10 is around the midpoint of the Likert scale, which indicates that these indicators might indirectly moderate DPP for the drivers. On the other hand, the remaining indicators (i.e., Bas1, Bas2, Bas3, Bas5, Bas6, and Bas7) have a mean value significantly lower than the midpoint of the Likert scale (2.5). These measures might affect the relationship between SCD and DPP on the basis & the foundation moderator. However, the fluctuating mean values indicate that further statistical analysis is required to determine the moderator effect between SC drivers and DPP.

The standard deviation values of Bas 4, 8, 9, and 10 show that a range of collected data is covered by 1.5 standard deviations above of mean value approximately. For the rest of the indicators (i.e., Bas1, Bas2, Bas3, Bas5, Bas6, and Bas7), the data is dispersed by 1.0 standard deviation lower than the mean value approximately. In addition, the Kurtosis and Skewness of four measures (i.e., Bas2, Bas3, Bas6, and Bas7) were above ± 2, which might not present

normal distribution for the indicators. The rest of the basis & foundation variable measures were within -2 to +2, which might be considered a normal distribution for the measures. However, it is necessary to conduct a normality analysis to ensure the normality assumption is not violated.

Table 4-9- Descriptive statistics of basis and foundation variable as a moderator.

	No	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
Bas1	212	0	5	0.95	0.827	0.097	-1.534
Bas2	212	0	5	0.33	0.649	3.330	17.179
Bas3	212	0	5	0.32	0.661	3.318	16.315
Bas4	212	1	5	2.74	1.385	0.270	-1.116
Bas5	212	1	5	1.55	0.508	-0.082	-1.733
Bas6	212	0	5	0.25	0.532	3.012	13.915
Bas7	212	0	5	0.33	0.640	3.410	18.171
Bas8	212	0	5	2.50	1.989	-0.002	-1.676
Bas9	212	0	5	2.59	1.820	-0.260	-1.322
Bas10	212	0	5	2.52	1.778	-0.123	-1.356

4.5.9 Descriptive analysis of market

This section has summarised the descriptive analysis of the market variable between SC drivers and DPP. To measure the market effect between SC drivers and DPP, eight different measures were identified whereby eight questions were included in the questionnaire to address their variables accordingly. Table 4-10 shows the descriptive analysis of the market variable as moderator, including mean, standard deviation, kurtosis, and skewness. Participants have considered the maximum and minimum values of the Likert scale for all measures of this variable.

Furthermore, the mean value of all measures of the market moderator is lower than the midpoint of the Likert scale (2.5), which indicates that these measures might not significantly moderate the relationship between SCD and DPP. However, the fluctuating mean values indicate that further statistical analysis is required to determine the effect of the market moderator between SC drivers and DPP.

Furthermore, the standard deviation values of Mark 1, 4, 5, and 8 show that a range of collected data is covered between 0.5 to 1 standard deviation above of mean value approximately. For the rest of the indicators (i.e., Mark2, Mark3, Mark6, and Mark7,) the data is dispersed around the mean by approximately 0.6 standard deviations lower than the mean value. In addition, the Kurtosis and Skewness of four measures (i.e., Bas2, Bas3, Bas6, and
Bas7) were above ± 2, which might not present normal distribution for the indicators. The rest of the basis & foundation variable measures were within the range of -2 to +2, which might be considered a normal distribution for the measures. However, it is necessary to conduct a normality analysis to ensure the normality assumption is not violated.

Table 4-10- Descriptive statistics of market variable as a moderator.

	No	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
Mark1	212	0	5	0.30	0.554	3.371	23.031
Mark2	212	0	5	0.83	1.044	1.583	2.804
Mark3	212	0	5	0.79	1.055	1.451	2.240
Mark4	212	0	5	0.39	0.703	2.929	12.697
Mark5	212	0	5	0.31	0.572	3.253	20.435
Mark6	212	0	5	0.79	1.347	1.934	2.870
Mark7	212	0	5	1.10	1.465	1.360	0.845
Mark8	212	0	5	0.34	0.638	3.311	17.907

4.5.10 Descriptive analysis of business & enterprise

This section has summarised the descriptive analysis of the business & enterprise variable between SC drivers and DPP. To determine the effect of business & enterprise between SC drivers and DPP, eight different measures were identified. Eight questions were included in the questionnaire to address their variables accordingly. Table 4-11 shows the descriptive analysis of the business & enterprise variable as moderators, including mean, standard deviation, kurtosis, and skewness. Participants have considered the maximum and minimum values of the Likert scale for all measures of this variable.

The mean value of all measures except Bus 4 and 5 is around the midpoint of the Likert scale (2.5), indicating that those indicators might have an average of the basis & foundation moderator on the relationship of the SCD and DPP. On the other hand, the mean value of the

remaining indicators is lower than the midpoint of the Likert scale, which shows that those indicators have a lower effect on the relationship between the SCD and DPP. Fluctuating mean values (upper and lower of 2.5) around the midpoint demonstrated that further statistical analysis is required to determine the effect of moderators on the relationship between SC drivers and DPP.

The highest standard deviations in this factor belonged to Bus 4, 5, and 7, showing that a range of collected data is approximately two standard deviations higher than the mean value. The rest of the indicators have had standard divisions lower than one, which showed that the collected data has deviated around the mean value. In addition, the Kurtosis and Skewness of Bus 4 and 5 variables are within the range of -2 to +2. Hence, it might be considered a normal distribution for the measures. On the other hand, the remaining variables have had Kurtosis and Skewness higher than 2, which might not present normal distribution of the collected data for these indicators. Finally, it is necessary to conduct a normality analysis to ensure the normality assumption is not violated.

Table 4-11- Descriptive statistics of business and enterprise variables as a moderator.

	No	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
Bus1	212	0	5	0.28	0.545	3.619	25.373
Bus2	212	0	5	0.39	0.703	2.929	12.697
Bus3	212	0	5	0.31	0.572	3.253	20.435
Bus4	212	0	5	1.98	1.819	0.300	-1.388
Bus5	212	0	5	2.35	1.753	0.177	-1.390
Bus6	212	0	5	0.42	0.901	3.274	12.167
Bus7	212	0	5	0.77	1.362	1.987	2.960
Bus8	212	0	5	0.30	0.626	3.653	20.485

4.6 Normality Test

The normality test is an essential stage for the continuous data to decide what types of statistical methods should be selected for data analysis and measure central tendency. The parametric tests are used for the normally distributed data, whereas the nonparametric approaches are applied for a data set that does not follow a normal distribution (Mishra et al. 2019a).

This section examined the normality test of collected data using the Kolmogorov-Smirnov test and the Shapiro-Wilk test.

Kolmogorov-Smirnov (K-S test) test calculates the most significant vertical distance between the empirical cumulative distribution of the sample and the normal cumulative distribution function as a reference. The K-S test is classified as an empirical distribution function that calculates the biggest vertical distance between the frequencies of empirical distribution functions between two samples or groups of samples (Dimitrova et al. 2020).

The Shapiro- Wilk test is another test to investigate whether the collected data is normally distributed. Shapiro–Wilk test is one of the most precise and reliable tests to check the normality of the collected data, which works significantly efficient for the smaller sample size. Shapiro–Wilk test is categorised as a regression-type test that calculates the correlation of sample order statistics (Razali et al. 2011).

For both the K-S test (D_n) and Shapiro-Wilk test (W), the null hypothesis is tested for the test statistic at the chosen confidence level of α (for this study is 95%). For both tests, the following hypotheses were considered:

Null Hypothesis (H_0; $P \geq 0.05$): The samples have been collected from a normally distributed population.

Against

(H_1; $P < 0.05$): The samples have not been collected from a normally distributed population.

For instance, if the P-value of the test statistic is more significant than 0.05, it can be interpreted that the collected data is taken from a normally distributed population. Conversely, if the P-value of the test statistic is less than 0.05, the null hypothesis is rejected, which shows that the collected data is not normally distributed (Shapiro and Wilk 1965; Razali et al. 2011; Dimitrova et al. 2020).

Table 4-2-Descriptive statistics of production deriver. Table 4-12 shows the outcome of the normality test for the collected data, including the K-S test and Shapiro-Wilk test using SPSS software (IBM SPSS Statistics V.26). The computed P-value of all collected data is significant ($P< 0.05$) for both K-S and Shapiro-Wilk approaches, and therefore their null hypothesis is rejected. In this case, it can be interpreted that collected data were not obtained from a normally distributed population or did not follow a normal distribution pattern.

Table 4-12-Normality test of collected data.						
	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Test-Statistic (Dn)	df	Test-Statistic (Dn)	df	Test-Statistic (Dn)	df
Pro1	0.148	212	0.000	0.889	212	0.000
Pro2	0.204	212	0.000	0.894	212	0.000
Pro3	0.198	212	0.000	0.885	212	0.000
Pro4	0.158	212	0.000	0.888	212	0.000
Pro5	0.158	212	0.000	0.905	212	0.000
Pro6	0.159	212	0.000	0.884	212	0.000
Pro7	0.163	212	0.000	0.887	212	0.000
Inv1	0.153	212	0.000	0.897	212	0.000
Inv2	0.154	212	0.000	0.880	212	0.000
Inv3	0.156	212	0.000	0.898	212	0.000
Inv4	0.167	212	0.000	0.886	212	0.000
Inv5	0.143	212	0.000	0.891	212	0.000
Inv6	0.167	212	0.000	0.893	212	0.000
Loc1	0.151	212	0.000	0.890	212	0.000
Loc2	0.154	212	0.000	0.893	212	0.000
Loc3	0.177	212	0.000	0.889	212	0.000
Loc4	0.152	212	0.000	0.884	212	0.000
Loc5	0.164	212	0.000	0.885	212	0.000
Inf1	0.164	212	0.000	0.880	212	0.000
Inf2	0.148	212	0.000	0.899	212	0.000
Inf3	0.152	212	0.000	0.878	212	0.000
Inf4	0.182	212	0.000	0.886	212	0.000
Inf5	0.179	212	0.000	0.895	212	0.000
Inf6	0.159	212	0.000	0.899	212	0.000
Inf7	0.143	212	0.000	0.892	212	0.000
Inf8	0.140	212	0.000	0.883	212	0.000
Inf9	0.170	212	0.000	0.895	212	0.000
Tran1	0.140	212	0.000	0.889	212	0.000
Tran2	0.171	212	0.000	0.898	212	0.000
Tran3	0.161	212	0.000	0.893	212	0.000
DPP1	0.199	212	0.000	0.904	212	0.000
DPP2	0.167	212	0.000	0.885	212	0.000
DPP3	0.154	212	0.000	0.888	212	0.000
DPP4	0.167	212	0.000	0.890	212	0.000
DPP5	0.152	212	0.000	0.890	212	0.000
DPP6	0.168	212	0.000	0.884	212	0.000
DPP7	0.154	212	0.000	0.887	212	0.000
DPP8	0.154	212	0.000	0.902	212	0.000
Tscv1	0.139	212	0.000	0.894	212	0.000
Tscv2	0.154	212	0.000	0.892	212	0.000

Tscv3	0.154	212	0.000	0.918	212	0.000
Tscv4	0.152	212	0.000	0.898	212	0.000
Bas1	0.242	212	0.000	0.788	212	0.000
Bas2	0.416	212	0.000	0.521	212	0.000
Bas3	0.427	212	0.000	0.516	212	0.000
Bas4	0.161	212	0.000	0.884	212	0.000
Bas5	0.356	212	0.000	0.656	212	0.000
Bas6	0.459	212	0.000	0.494	212	0.000
Bas7	0.416	212	0.000	0.513	212	0.000
Bas8	0.227	212	0.000	0.830	212	0.000
Bas9	0.207	212	0.000	0.865	212	0.000
Bas10	0.186	212	0.000	0.884	212	0.000
Bus1	0.436	212	0.000	0.490	212	0.000
Bus2	0.393	212	0.000	0.560	212	0.000
Bus3	0.426	212	0.000	0.526	212	0.000
Bus4	0.205	212	0.000	0.851	212	0.000
Bus5	0.233	212	0.000	0.879	212	0.000
Bus6	0.399	212	0.000	0.497	212	0.000
Bus7	0.347	212	0.000	0.616	212	0.000
Bus8	0.426	212	0.000	0.488	212	0.000
Mark1	0.424	212	0.000	0.510	212	0.000
Mark2	0.258	212	0.000	0.753	212	0.000
Mark3	0.311	212	0.000	0.747	212	0.000
Mark4	0.393	212	0.000	0.560	212	0.000
Mark5	0.426	212	0.000	0.526	212	0.000
Mark6	0.340	212	0.000	0.636	212	0.000
Mark7	0.264	212	0.000	0.749	212	0.000
Mark8	0.403	212	0.000	0.524	212	0.000
a. Lilliefors Significance Correction						

4.7 Reliability Statistics

This section assessed the reliability and internal consistency of collected data using total-item correlation and Cronbach's alpha. In addition, the inter-item correlation between measurers of each variable has been assessed to determine whether they were correlated to each other to measure the variable.

Cronbach's alpha is arguably the most common metric applied to evaluate the internal consistency reliability of scores derived from a scale. Researchers use Cronbach's Alpha criterion to show the internal consistency of their collected data. The value of Cronbach's alpha varies from zero to one, while the accepted limit must equal and be higher than 0.7

(Cronbach′s Alpha ≥ 0.7) (Moskal and Leydens 2000; Lance et al. 2006; Lavrakas 2008; Cho and Kim 2015; Bae 2020).

According to (Gliem and Gliem 2003), removing or omitting any items from the study must enhance the Cronbach's Alpha score; otherwise, the item should not be removed from the construct. In other words, if the quality criterion of the questionnaire (like Cronbach's Alpha) has been reduced by removing the measure or item from a construct, it is not permitted to remove the measure. Contrariwise, if omitting an item enhances the quality criterion of the questionnaire, it is allowed to remove the item or measure from a construct; however, the factor loading should also be considered.

Hajjar (2018) stated that to assess the internal consistency of any variable, the total item correlation must be considered to ensure the reliability of the measures or items within the variable has not been violated. She also considered four other tests to check the internal consistency, including Cronbach's alpha (without removing any items), inter-item correlation, item-total correlation, and Cronbach's alpha if the item is deleted.

According to (Henrysson 1963), the total-item correlation measures any inconsistency between the items. Hajjar (2018) stated the acceptable value of total-item correlation is higher than 0.5. Several researchers applied the total-item correlation along with the Cronbach's alpha (α_{Σ}) to demonstrate the internal consistency of their study (Bae 2020; Doan 2020; Fadaki et al. 2020; Mikhail et al. 2020; Reklitis et al. 2021).

However, Revelle and Zinbarg (2008) have not considered the inter-item correlation as a reliable method to check the reliability of the data due to the severe existing problem in identifying the internal consistency between the cases. They mentioned that item-item (i.e., inter-item) correlation does not differentiate between the measures of the variable, and each item is correlated with only a small proportion of the other items.

The inter-item correlation test measures the relation between items of each variable separately. Therefore, the effect of all other variables and their measures has been violated and neglected in a construct. Later, Tang et al. (2014) mentioned that the average inter-item correlation also does not measure and reflect the inconsistency between the test items or variables. The inter-item correlation test conducted by SPSS merely considers one variable within its measures, neglecting the effect of inter-correlation between all other variables and their measures. Therefore, this chapter has not studied the inter-item correlation due to its shortcomings. Nevertheless, in the next chapter, the inter-item correlation based on the Fornell-Larcker criterion has been studied using SmartPLS to ensure the reliability of the construct has not been violated.

The issue was resolved using SmartPLS software (the CFA approach), and the entire construct with various variables was analysed simultaneously. Hence, in the next chapter, the SmartPLS software has been used to produce more reliable results and determine which measures or indicators would be permanently removed from the construct to enhance the study's reliability.

4.8 Cronbach's alpha of all variables

The calculated Cronbach's Alpha statistics using SPSS software (IBM SPSS Statistics V.26) for the entire construct, including drivers and moderators, are shown in Table 4-13. The second column represents Cronbach's alpha (α_{Σ}) which is applied to find alpha based on the covariance matrix. Whereas the third column represents Cronbach's Alpha Based on Standardized (α_{R}) which computes alpha based on the correlations among variables or simply correlation matrix (Landau and Everitt 2003; Falk and Savalei 2011).

All SC drivers, TSCV, and DPP except transportation drivers have had a satisfactory level of stability and showed internal consistency between their variables. Furthermore, the moderators were also shown the acceptance limit of the internal consistency when the standardised items were applied except for the basis & foundation variable.

Although the preliminary evaluation of reliability between each factor has demonstrated a satisfactory level of consistency between collected data, further analysis is required to assess the measures' reliability and factor loading evaluation. Hence SEM through PLS analysis was applied in the next chapter to ensure whether omitting items from the construct caused increase or decrease of Cronbach's Alpha.

Table 4-13- Reliability Statistics of the variables

Variables	Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	No of Items
Production Driver	0.806	0.804	7
Inventory Driver	0.777	0.777	6
Location Driver	0.755	0.756	5
Information Driver	0.801	0.801	9
Transportation Driver	0.547	0.544	3
DPP	0.745	0.740	8
TSCV	0.813	0.802	4
Basis & Foundation	0.079	0.420	10
Business & Enterprise	0.538	0.681	8
Market	0.594	0.721	8

4.8.1 Reliability Statistics of Production Driver

Table 4-14 shows the Cronbach's Alpha (CA) in which the items or measures were deleted from the proposed construct due to their lower total inter-correlation values. Principally, Cronbach's Alpha has been affected positively or negatively by removing measures from a construct or adding variables to a construct. The total value of Cronbach's Alpha of the production driver was 0.806 (see table 4-13).

By removing Pro2 and Pro3 from the questionnaire, the value of Cronbach's Alpha was enhanced to 0.832 and 0.827, respectively. The item-total correlation for Pro2 and Pro3 reported 0.224 and 0.271, respectively, lower than 0.5. Hence, the items might be omitted from the analysis, and these items might not measure the proposed construct. Furthermore, Pro5 also increased the value of Cronbach's Alpha from 0.806 to 0.812, which did not show any significant increase, while the item-total correlation of pro5 is lower than 0.5. Therefore, removing Pro5 from the questionnaire might not enhance the reliability.

In conclusion, based on the current analysis, three items (i.e., measures or questions), including Pro2, Pro3, and Pro5, were listed to remove from the construct to enhance the study's reliability. Although deleting these items might improve the reliability of the study, further analysis has been conducted in the next chapter to ensure the internal consistency was not violated.

Table 4-14- Item-total statistics of production driver.

Cronbach's Alpha: 0.806

Cronbach's Alpha Based on Standardized Items: 0.804

Measures	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Pro1	17.86	30.378	0.791	0.729	0.733
Pro2	17.62	39.023	0.224	0.077	0.832
Pro3	18.03	37.880	0.271	0.093	0.827
Pro4	17.78	31.934	0.673	0.585	0.756
Pro5	18.07	37.010	0.355	0.158	0.812
Pro6	17.92	30.789	0.744	0.789	0.742
Pro7	17.84	30.265	0.794	0.832	0.733

4.8.2 Reliability Statistics of inventory driver

Table 4-15 shows the quality criteria, including Cronbach's Alpha, in which the items or measures were deleted from the construct due to their lower total inter-correlation values. Principally, Cronbach's Alpha has been affected positively or negatively by removing measures from a construct or adding variables to a construct. The total value of CA of the inventory driver was 0.777.

By removing Inv3 and Inv1 from the proposed construct, the value of CA was increased to 0.840 and 0.816, respectively. In addition, the values of item-total correlation for both items (Inv3 and Inv1) were lower than 0.5. Therefore, Inv3 and Inv1 might be removed from the proposed construct and questionnaire due to their lowest values of total inter-correlation and enhancing the reliability of the questionnaire. At the same time, all other variables and the related questions were retained in the construct and questionnaire survey. Although deleting these items might enhance the reliability of the study, further analysis has been conducted in the next chapter to ensure the internal consistency was not violated.

Table 4-15- Item-total statistics of inventory driver.

Cronbach's Alpha: 0.777

Cronbach's Alpha Based on Standardized Items: 0.777

Measures	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Inv1	14.66	28.576	0.213	0.081	0.816
Inv2	14.75	22.025	0.708	0.696	0.694
Inv3	14.90	30.274	0.098	0.046	0.840
Inv4	14.93	22.830	0.671	0.529	0.705
Inv5	14.73	21.818	0.765	0.766	0.680
Inv6	14.84	21.478	0.810	0.791	0.668

4.8.3 Reliability Statistics of location driver

Table 4-16 shows the quality criteria, including Cronbach's Alpha, if items or measures were deleted from the construct due to their lower total inter-correlation values.

The total value of the CA of the location driver was 0.755. Removing Loc3 from the construct caused an increase in the Cronbach's Alpha value from 0.755 to 0.820. In addition, the total

item correlation of Loc3 is 0.085, which was lower than the accepted limit (i.e., 0.5). Therefore, omitting the Loc3 item from the questionnaire might enhance the internal consistency of the collected data. Furthermore, removing Loc2 from the questionnaire increased the value of Cronbach's Alpha from 0.755 to 0.790, which was insignificant. Although the Cronbach's Alpha has risen slightly and the total-item correlation of Loc2 (0.280) was lower than the accepted limit (i.e., 0.5), removing Loc2 from the collected data might not affect the internal consistency of the questionnaire significantly. Consequently, in this step, merely Loc3 can be designated for withdrawal from the proposed construct and collected data due to their lowest values of total inter-correlation to enhance the collected data's reliability.

All other variables and the related questions were retained in the construct and questionnaire survey. Although total-item correlation showed that removing a minimum of one measure or item was permitted, the analysis in the next chapter provided a better understanding of determining which item can be drawn from the construct. Because, in the current test, each driver has been analysed separately within its measures, and the effect of inter-correlation between all five drivers and their measures is neglected. This issue was resolved using SmartPLS software (the CFA approach), and the entire construct with various drivers and variables was analysed. Hence, the SmartPLS software has been used in the next chapter to produce more reliable results and determine which measures or indicators should be removed permanently from the construct.

Table 4-16- Item-total statistics of location driver

Cronbach's Alpha:0.755

Cronbach's Alpha Based on Standardized Items: 0.756

Measures	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Loc1	12.18	15.778	0.712	0.741	0.640
Loc2	12.02	20.009	0.286	0.084	0.791
Loc3	12.05	20.978	0.196	0.085	0.820
Loc4	12.20	15.344	0.736	0.706	0.629
Loc5	12.06	15.053	0.775	0.749	0.613

4.8.4 Reliability Statistics of information driver

Table 4-17 shows the quality criteria, including Cronbach's Alpha, in which the items or measures were deleted from the construct due to their lower total inter-correlation values. Principally, Cronbach's Alpha has been affected positively or negatively by removing measures from a construct or adding variables to a construct.

As discussed, a minimum of two criteria must be checked before omitting any item from the questionnaire. The total inter-correlation of the item must be lower than 0.5, and removing the items must enhance the CA of the construct. In this case, it is permitted to remove the item or measure from the construct to improve the internal consistency and reliability of the data set. The total value of the CA of the information driver was 0.774. By removing Inf4 and Inf5 from the collected data, the values of Cronbach's Alpha were increased to 0.802 and 0.782, respectively. In addition, the values of the item-total correlation of the Inf5 were lower than 0.5. Therefore, this item was selected to remove from the questionnaire.

However, Inf 2 has a lower impact on enhancing the value of Cronbach's Alpha. It might be that releasing this item from the collected data does not significantly increase the collected data's reliability. Nevertheless, the construct and questionnaire survey retained all other variables and related questions. However, total-item correlation and CA (if items are deleted) showed that removing the measures is permitted. Nevertheless, the analysis in the next chapter created a better understanding of which item can be removed from the construct.

In the current test, each driver has been analysed separately within its measures, and the effect of inter-correlation between all five drivers and their measures is neglected. This issue was resolved using SmartPLS software (the CFA approach), and the entire construct with various drivers and variables was analysed. Hence, the SmartPLS software has been used in the next chapter to produce more reliable results to determine which measures or indicators should be permanently removed from the construct.

Table 4-17- Item-total statistics of information driver.

Cronbach's Alpha:0.774

Cronbach's Alpha Based on Standardized Items: 0.774

Measures	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Inf1	24.06	42.731	0.715	0.734	0.712

Inf2	23.96	50.027	0.318	0.168	0.772
Inf3	24.08	43.998	0.631	0.707	0.726
Inf4	24.03	53.800	0.113	0.069	0.802
Inf5	23.95	51.372	0.250	0.704	0.782
Inf6	24.17	49.955	0.327	0.151	0.771
Inf7	24.12	43.653	0.693	0.685	0.717
Inf8	24.05	42.741	0.720	0.730	0.712
Inf9	23.94	48.215	0.416	0.718	0.759

4.8.5 Reliability Statistics of transportation drivers

Table 4-18 shows the quality criteria, including Cronbach's Alpha, in which the items or measures were deleted from the construct due to their lower total inter-correlation values. Principally, Cronbach's Alpha has been affected positively or negatively by removing measures from a construct or adding variables to a construct.

As discussed, a minimum of two criteria must be checked before omitting any item from the questionnaire. The total inter-correlation of the item must be lower than 0.5, and removing the item must enhance the Cronbach's Alpha of the questionnaire. In this case, it is permitted to remove the measure from the questionnaire (i.e., construct) to improve the internal consistency and reliability of the collected data.

The total value of CA of transportation driver was 0.547. By removing Tran2 from the collected data, the value of Cronbach's Alpha was increased to 0.765. In addition, the item's item-total correlation values were lower than 0.5. Therefore, this item was selected to remove from the questionnaire.

Nevertheless, the construct and questionnaire survey retained all other variables and related questions. Although deleting the item might enhance the reliability of the study, further analysis has been conducted in the next chapter to ensure the internal consistency was not violated.

Table 4-18- Item-total statistics of transportation driver.					
Cronbach's Alpha:0.547 Cronbach's Alpha Based on Standardized Items: 0.544					
Measures	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Tran1	6.03	4.392	0.517	0.391	0.169
Tran2	6.05	6.737	0.130	0.020	0.765
Tran3	5.89	4.656	0.478	0.384	0.246

4.8.6 Reliability Statistics of DPP

Table 4-19 shows the quality criteria, including Cronbach's Alpha, in which the items or measures were deleted from the construct due to their lower total inter-correlation values.

As discussed, a minimum of two criteria must be checked before omitting any item from the questionnaire. Firstly, the total inter-correlation of the item must be lower than 0.5. Secondly, removing the item must enhance the Cronbach's Alpha of the questionnaire. In this case, it is permitted to remove the item or measure from the questionnaire to improve the internal consistency and reliability of the collected data.

The total value of Cronbach's Alpha of the DPP variable was 0.745. By removing DPP1, DPP4, and DPP5 from the collected data, the value of Cronbach's Alpha was increased to 0.750, 0.774, and 0.757, respectively. In addition, the item-total correlation values of these items were lower than 0.5. Nevertheless, for DPP1 and DPP5, the values of Cronbach's Alpha have not increased significantly; therefore, removing these items might not enhance the reliability of the questionnaire survey. On the other hand, omitting DPP4 from the questionnaire might substantially improve the collected data's internal consistency.

All other variables and their related questions must be retained in the construct and questionnaire survey. Although deleting the items might enhance the reliability of the study, further analysis using SmartPLS software has been conducted in the next chapter to ensure the internal consistency was not violated.

Table 4-19- Item-total statistics of DPP variable.					
Cronbach's Alpha:0.745 Cronbach's Alpha Based on Standardized Items: 0.740					
Measures	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
DPP1	21.17	40.391	0.263	0.102	0.750
DPP2	21.25	34.217	0.595	0.607	0.687
DPP3	21.27	33.517	0.648	0.604	0.677
DPP4	21.15	42.599	0.119	0.121	0.774
DPP5	21.27	40.264	0.232	0.182	0.757
DPP6	21.03	34.141	0.617	0.527	0.684
DPP7	21.31	32.329	0.729	0.768	0.659
DPP8	21.30	38.447	0.360	0.221	0.733

4.8.7 Reliability Statistics of TSCV variable

Table 4-20 shows the quality criteria, including Cronbach's Alpha, in which the items or measures were deleted from the construct due to their lower total inter-correlation values.
As discussed, a minimum of two criteria must be checked before omitting any item from the questionnaire. Firstly, the total inter-correlation of the item must be lower than 0.5. Secondly, removing the item must enhance the Cronbach's Alpha of the questionnaire. In this case, it is permitted to remove the item or measure from the questionnaire to improve the internal consistency and reliability of the collected data.

The total value of Cronbach's Alpha of the TSCV variable was reported as 0.804. By removing Tscv3 from the collected data, the value of CA was significantly increased to 0.940. In addition, the item's item-total correlation values were lower than 0.5. Hence, Tscv3 might be selected to remove from the questionnaire to enhance the collected data's internal consistency. Nevertheless, all other variables and their related questions must be retained in the construct and questionnaire survey. Although deleting the item might enhance the reliability of the study, further analysis using SmartPLS software has been conducted in the next chapter to ensure the internal consistency was not violated.

Table 4-20- Item-total statistics of TSCV variable.					
Cronbach's Alpha: 0.813					
Cronbach's Alpha Based on Standardized Items: 0.802					
Measures	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Tscv1	8.76	10.162	0.833	0.818	0.661
Tscv2	8.96	10.240	0.811	0.719	0.672
Tscv3	8.89	16.328	0.176	0.061	0.940
Tscv4	8.90	10.482	0.790	0.800	0.684

4.8.8 Reliability Statistics of basis & foundation moderator

Table 4-21 shows the quality criteria, including Cronbach's Alpha, in which the items or measures were deleted from the construct due to their lower total inter-correlation values. The CA has been affected positively or negatively by removing measures from a construct or adding variables to a construct. The calculated Cronbach's Alpha statistics using SPSS software (IBM SPSS Statistics V.26) included negative and positive values.

The negative value of CA was obtained based on a negative average covariance among the items, which might violate the reliability of model assumptions. However, according to the prior discussion (see chapter 3-section 3.14.2), this thesis's selected analysis (i.e., PLS/SEM) is variance-based. The number of samples is insufficient to conduct the CB/SEM analysis. Hence, the attained results of CA based on a negative covariance might not demonstrate the actual reliability of the collected data.

Suppose the inter-correlation of the item is low (lower than 0.5), and removing that item enhances the quality criteria (i.e., CA) of the questionnaire. In that case, it is allowed to remove the measure from the construct or variable.

Bas2, Bas3, Bas6, and Bas7's inter-correlation was higher than 0.5, which shows that they might not be removed from the construct due to their negative covariance CA. Furthermore, the total value of Cronbach's Alpha of basis & foundation moderator was 0.107. While removing Bas1, 4, 5, and Bas10 from the proposed construct caused an enhanced value of CA from 0.107 to 0.160, 0.230, 0.130, and 0.330, respectively. In addition, for the Bas1, 4, 5, and Bas10 measures, the values of total-item correlation were lower than the accepted limit (i.e.,

0.5). In this case, principally, it allowed removing the measures due to their lowest values of total inter-correlation. However, omitting these variables from the collected data might not significantly enhance the reliability of the questionnaire survey.

Although total-item correlation and Cronbach's Alpha indicated removing the measures or items permitted, the conducted analysis in the next chapter created a better understanding of which items should withdraw from the construct. Because, in the current test, each driver has been analysed separately within its measures, and the effect of inter-correlation between all five drivers and their measures is neglected. The issue was resolved using SmartPLS software (the CFA approach), and the entire construct with various drivers and variables was analysed. Hence, in the next chapter, the SmartPLS software has been used to produce more reliable results to determine which measures or indicators can be permanently removed from the construct.

Table 4-21- Item-total statistics of basis & foundation moderator

Cronbach's Alpha:0.107

Cronbach's Alpha Based on Standardized Items: 0.451

Measures	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Bas1	13.13	16.43	-0.10	0.04	0.16
Bas2	13.75	14.67	0.27	0.66	0.02
Bas3	13.75	13.77	0.45	0.75	-0.052[a]
Bas4	11.33	16.25	-0.16	0.08	0.23
Bas5	12.53	16.54	-0.09	0.05	0.13
Bas6	13.83	14.61	0.38	0.73	0.00
Bas7	13.75	14.16	0.38	0.67	-0.022[a]
Bas8	11.58	10.98	0.11	0.16	0.01
Bas9	11.49	12.32	0.06	0.13	0.07
Bas10	11.55	16.47	-0.22	0.09	0.33

[a]: The value is negative due to a negative average covariance among items. This violates reliability model assumptions.

4.8.9 Reliability Statistics of business & enterprise moderator

Table 4-22 shows the quality criteria, including Cronbach's Alpha, in which the items or measures were deleted from the construct due to their lower total inter-correlation values.

Principally, Cronbach's Alpha has been affected positively or negatively by removing measures from a construct or adding variables to a construct.

The total value of Cronbach's Alpha of business & enterprise moderator was 0.538. It can be observed that removing indicators (i.e., measures) might not significantly improve the Cronbach's Alpha of this moderator. In addition, by checking the total-item correlation of the measures, it can be realised that most of the measures have a total-item correlation higher than the accepted limit (i.e., 0.5) or near the accepted limit except Bus2. Removing these measures from the collected data is not allowed in this case. In other words, the reliability analysis of the moderator alone (without considering the effect of other variables) showed that omitting these variables from the collected data might not significantly enhance the reliability of the questionnaire survey because the Cronbach's Alpha was not increased significantly. Although deleting the item might not enhance the reliability of the questionnaire survey for this variable, further analysis using SmartPLS software has been conducted in the next chapter to ensure the internal consistency was not violated.

Table 4-22- Item-total statistics of business & enterprise moderator.

Cronbach's Alpha: 0.538

Cronbach's Alpha Based on Standardized Items: 0.681

Measures	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Bus1	6.52	18.289	0.290	0.515	0.512
Bus2	6.41	17.892	0.260	0.341	0.511
Bus3	6.49	17.891	0.355	0.577	0.500
Bus4	4.82	13.042	0.273	0.562	0.518
Bus5	4.44	13.111	0.295	0.617	0.501
Bus6	6.38	17.081	0.274	0.561	0.501
Bus7	6.02	15.009	0.291	0.452	0.490
Bus8	6.50	17.853	0.319	0.429	0.502

4.8.10 Reliability Statistics of the market moderator

Table 4-23 shows the quality criteria, including Cronbach's Alpha, in which the items or measures were deleted from the construct due to their lower total inter-correlation values.

Principally, Cronbach's Alpha has been affected positively or negatively by removing measures from a construct or adding variables to a construct.

The total value of Cronbach's Alpha of market moderator was 0.594. It can be realised that by removing Mark7, the value of Cronbach's Alpha slightly increased from 0.594 to 0.665. Thus, it is necessary to check the total-item correlation. The total-item correlation values of this item were incredibly lower than the accepted limit (i.e., 0.5). In this case, it is allowed to remove the measure from the collected data due to their lowest values of total inter-correlation. On the other hand, Mark 6 has the total-item correlation (i.e., 0.111) lower than the accepted limit (0.5), but removing this measure will not improve the CA significantly.

Hence, this item might remain in the construct.

Although the conducted analysis shows that removing the measure or item might enhance the questionnaire survey's reliability, the analysis in the next chapter created a better understanding of determining which items should remove from the construct. Because, in the current test, each driver has been analysed separately within its measures, and the effect of inter-correlation of other SC drivers and moderators is neglected. The issue was resolved using SmartPLS software (the CFA approach), and the entire construct with various drivers and variables was analysed. Hence, in the next chapter, the SmartPLS software has been used to produce more reliable results and determine which measures or indicators can remove from the construct permanently.

Table 4-23- Item-total statistics of the market moderator.

Cronbach's Alpha: 0.594

Cronbach's Alpha Based on Standardized Items: 0.721

Measures	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Mark1	4.55	13.613	0.519	0.548	0.533
Mark2	4.02	13.379	0.206	0.360	0.590
Mark3	4.06	12.873	0.271	0.348	0.570
Mark4	4.47	12.923	0.519	0.528	0.516
Mark5	4.55	13.424	0.546	0.646	0.526
Mark6	4.06	11.518	0.296	0.111	0.571
Mark7	3.75	12.916	0.093	0.098	0.665
Mark8	4.51	13.294	0.503	0.456	0.527

4.8.11 Concluded remarks of descriptive analyses

Figure 4-1shows the descriptive analysis and preliminary quality control of collected data applied in the study. The normality tests, including Kolmogorov-Smirnov and Shapiro-Wilk tests, have been conducted to prove that the collected data does not form normally distributed data. Hence, applying the non-parametric tests like a partial least square approach is required.

The descriptive analyses were applied, including mean, skewness, and kurtosis. Also, the initial quality criteria, including Cronbach's Alpha, total-item correlation, and Cronbach's Alpha if the item is deleted, were used to determine the internal consistency and reliability of the collected data. At the end of this section, the items were listed as candidates to be potentially removed from the construct to enhance the data set's quality and reliability. However, the suggested items were not removed from the construct in this stage to conduct accurate analyses and ensure the quality criteria were not violated.

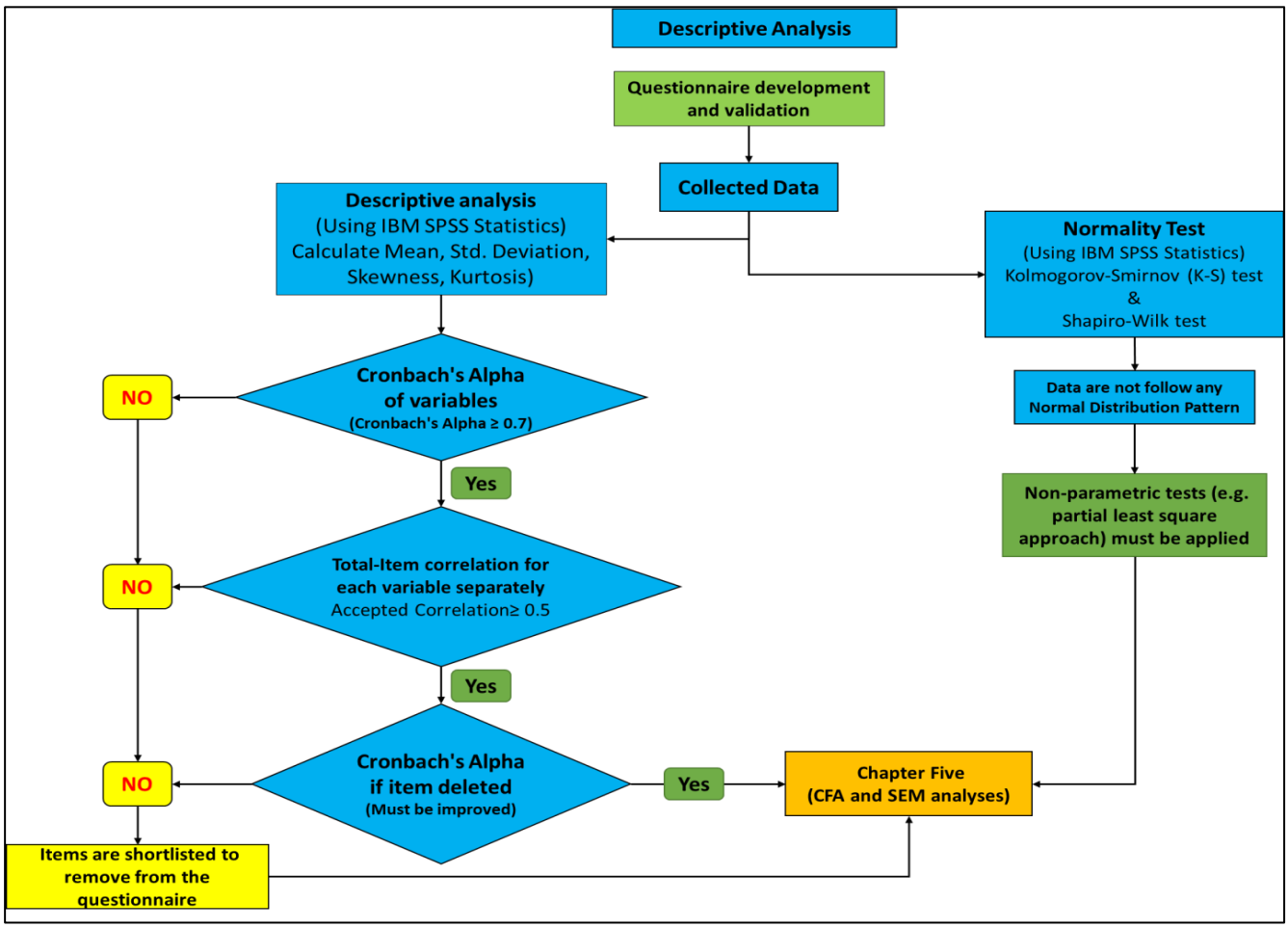


Figure 4-1- The descriptive analysis has been applied for this study.

Chapter 5 Confirmatory Factor Analysis (CFA) and Structural Equation Modelling (SEM)

5.1 Introduction

In this chapter, the descriptive analyses of the data, including confirmatory factor analysis (CFA) and structural equation modelling (SEM) using SmartPLS (V3), were performed. The preliminary and descriptive analyses were conducted in the previous chapter to comprehend how to enhance the reliability of the collected data. Hence, 19 items (measures) were shortlisted to eliminate from the construct to improve the collected data's internal consistency. However, the items were not omitted due to considering the inter-effect of items in the presence of all drivers and moderators.

In this chapter, the initial construct has been developed with 67 measures in 10 different variables (i.e., factors and moderators). In addition, five main hypotheses and twenty sub hypotheses have been proposed initially and proceeded to the CFA analysis using SmartPLS (V3). CFA is limited to the analysis of covariance and variance. Based on the variance extraction rule, if the variance factor loading of an item is equal to 0.7 or more significant than 0.7, the indicator must be kept in the construct (Hair 1995).

Hair et al. (2011) stated that the acceptable limit of factor loading for each item or measure must be 0.5 or greater. Any indicator with factor loading greater than 0.7 is considered an adequate measure or item. However, other researchers reported an acceptable limit for the factor loading is 0.5 or above 0.5 (Hulland 1999; Truong and McColl 2011). Chen and Tsai (2007) conducted a study on travel and tourism. Also, they considered 0.5 as an acceptable limit for the factor loading at the statistically significant test result of 95% (i.e., P-Value ≤ 0.5). Ertz et al. (2016) explored a study in pro-environmental consumer behaviour and considered the factor loading of 0.4 and above at the same statistical confidence level. Chin et al. (1997) and Hair et al. (2011) suggested a threshold of 0.6 for the standardised factor loading. Knekta et al. (2019) stated that factor loading is close to 0.7 or higher than the threshold limit of 0.7, meaning that factors were explained most of the items well by the

theorised factor. Finally, in this study, the threshold limit of 0.7 was considered in CFA at the confidence level of 0.05 (Factor Loading ≥ 0.7 @ P-value ≤ 0.05).

For the bootstrapping analysis, the basic setting of SmartPLS software was set up as follows: The subsamples value should be large enough to ensure the stability of results has been satisfied. Hence, the subsamples value for the bootstrapping test was considered 5,000. This analysis has considered basic bootstrapping, including outer loadings, path coefficient, outer weights, total effect, and indirect effect. This option is significantly faster, more suitable for the initial data analysis, and appropriate for large resamples (i.e., 5000). The "Bias Corrected and Accelerated (BCa) Bootstrap" has been selected (software default) because it is the most stable approach without spare computing time.

The bootstrapping approach with maximum iterations of 5000 has been applied to determine the weight of path coefficient and T-value of the proposed structure. The stop criterion should be a minimal value of 10^{-7} for the bootstrapping test (Hair et al. 2017).

In this study, the CFA has been conducted for the moderators and drivers separately, including partial least squares (PLS) and bootstrapping analyses to reduce the number of indicators from the proposed constructs and enhance their reliability and validity. This study demonstrated a minimum of three rounds of PLS and bootstrapping analyses to finalise the proposed constructs for the SC drivers without considering moderators. However, it could be possible to show more steps and rounds to complete the initial construct in this section. Still, it has been found that applying more than three rounds did not change the final results. Hence, three rounds have been selected to determine the final construct in which all elements have had the factor loading higher than 0.7, and all the quality criteria were satisfied.

According to (Hair et al. 2017), it is essential to have a minimum of three items or indicators per factor or variable. If three items have remained per each factor, the construct would be just a “defined model” with zero degrees of freedom, and it can be stated that the model is suitable for the study. While, if four items (or indicators) have remained per factor, it will create a positive degree of freedom in a construct called an over-identified model because there are more degrees of freedom than parameters.

This study has been considered to keep a minimum of three indicators per factor. Therefore, any factor (variable) with less than three items was removed from the construct. Finally, all remaining items (i.e., indicators) from the final construct of SC drivers were inserted into the factor analysis of the moderators to reduce the number of indicators and enhance the validity of the construct. Of course, in this stage, the number of items of SC drivers and their factor loading values have remained without any changes.

The SEM approach also has been applied to estimate the variables (unobserved values) via using observed variables and confirming the proposed hypotheses and related sub-hypotheses (Byrne 2013). To conduct covariance-based SEM (CB/SEM) for the proposed construct, it would be essential to collect a minimum of 670 observations (10 observations per indicator) for this study. While in this study, 212 applicants replied to the survey successfully, which shows that the collected data and number of samples were not large enough to conduct the CB/SEM analysis. Hence, the PLS/SEM has been selected to examine this study's proposed to construct and hypotheses. Moreover, the acquired results were reported in two approaches, including graphical and tabular representations.

5.2 Confirmatory Factor Analysis (CFA) of Supply chain drivers

In this section, the confirmatory factor analysis (CFA) is conducted to estimate the factor loading of SC drivers at a 95% confidence level. The value of factor loading presents the level of a regression path from a variable to its indicators (Hair et al. 2011).

The partial least square analysis using SmartPLS (V3) software was applied to complete the CFA approach. The PLS algorithm with maximum iterations of 300 has been applied to determine the weight of factor loading of the proposed structure. Using the PLS algorithm's weighting scheme, the SmartPLS software provides a maximum proportion of the variance (R^2) for the endogenous variable like DPP and TSCV. In addition, it is necessary to define the "Stop Criterion" for the software to stop the change of the outer weights. In this case, the SmartPLS software pauses the outer weight between two consecutive iterations when it is smaller than the defined stop criterion. The stop criterion should be a minimal value as defined 10^{-7} for the PLS algorithm analysis and bootstrapping test.

This study developed the initial construct with 30 measures for five SC drivers, including information, location, production, transportation, and inventory. Also, the initial construct included DPP and TSCV variables with 8 and 4 measures or indicators, respectively. Each round of analysis consists of a minimum of five various studies, including the following tests:

1- Completing CFA via using the PLS algorithm and selecting factor item for the weighting scheme
2- Finding the factor loading of indicators as an outer weight of loading equal and higher than 0.7 @ $P - value \leq 0.05$
3- Checking the quality criteria of the construct (including Cronbach's Alpha ≥ 0.7, composite reliability (CR ≥ 0.7), and average variance extracted (AVE ≥ 0.5).

4- Applying bootstrapping analysis to evaluate the T-value of the pathway between indicators and factors ($T - vlaue \geq |\pm 1.96|$ @ $P - value \leq 0.05$)
5- Evaluating the path analysis between two variables (i.e., factors) using bootstrapping analysis ($T - vlaue \geq |\pm 1.96|$ @ $P - value \leq 0.05$)

5.2.1 CFA Round 1- PLS of initial construct

Figure 5-1 shows the CFA of the initial construct, including five SC drivers, DPP, and TSCV variables with their indicators. The yellow rectangle shows the indicators in this analysis, and the blue circle shows the factors or variables. The first round of confirmatory factor analysis (CFA) using the PLS algorithm demonstrated the outer weight of the indicators (the numbers between factor and indicators) as well as the path coefficient (the digits between two factors). However, the path coefficient and their related digits were not considered in this stage due to choosing the factor weighting scheme in the setting of the PLS algorithm. Many indicators showed outer factor loading lower than 0.7, which would be removed from the construct permanently to enhance the reliability and validity of the construct. To remove the selected indicators from the theoretical model, it was necessary to check the quality criteria at the first stage. In other words, the omitting process of indicators must significantly enhance the construct's quality; otherwise, the items should not be removed from the model. Although the initial PLS analysis shows that 18 indicators have outer factor loading lower than 0.7, removing all items in one round is impossible because the existing interactions between the items might enhance the outer factor loadings. Hence, the removal process was completed in three different stages.

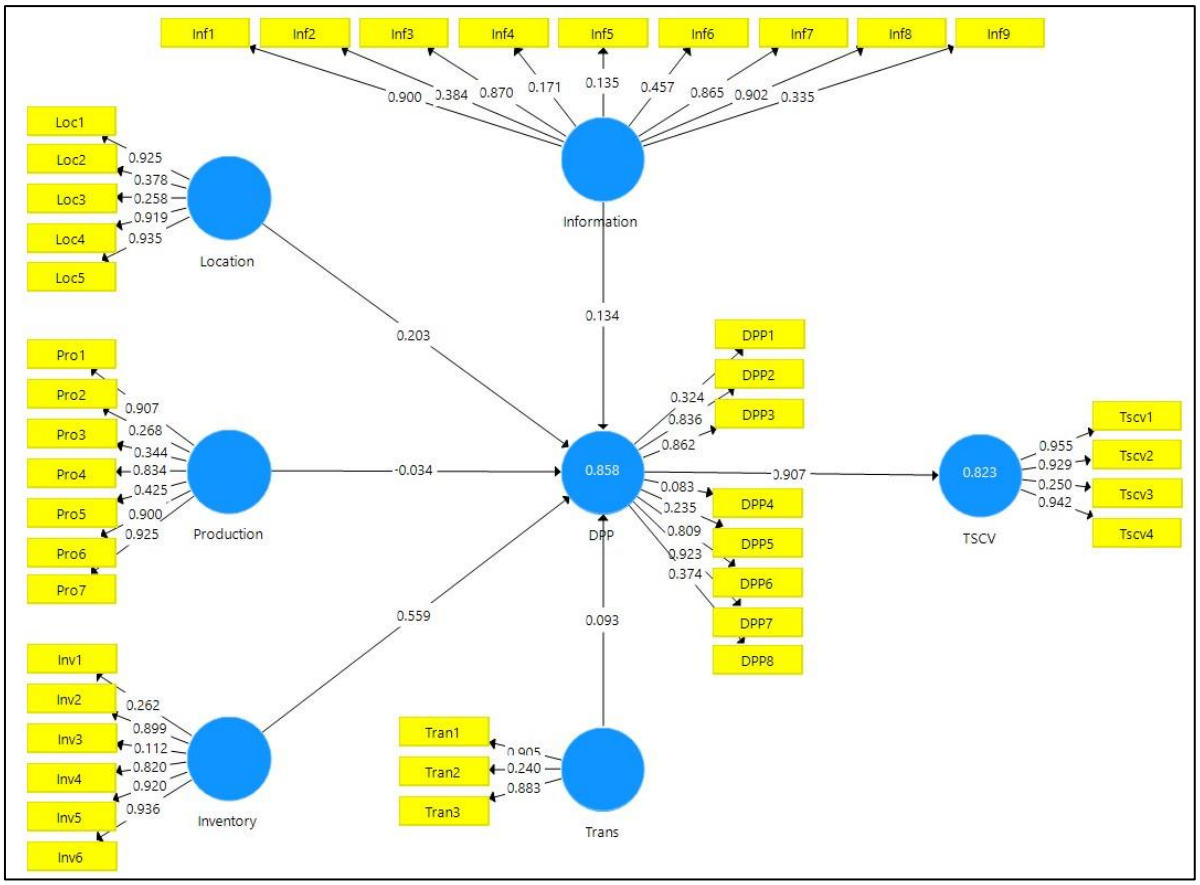


Figure 5-1- First round of confirmatory factor analysis (CFA) using PLS approach for an initial structural model of SC drivers.

Table 5-1 shows the initial construct's outer weight of factor loading, including five SC drivers, DPP, and TSCV. Overall, 17 indicators have had an outer weight of factor (i.e., factor loading) lower than 0.7, highlighted in red. DPP had four indicators with outer factor loading less than 0.7, including DPP 1, 4, 5, and 8. DPP 4 had the lowest value of factor loading with 0.083. Hence, DPP4 was nominated to remove from the construct in the next round. The information driver also had four indicators with outer factor loading less than 0.7, including Inf 2, 4, 5, 6 and 9. Inf 5 had the lowest value of factor loading with 0.135. Hence, Inf 5 was nominated to be removed from the construct in the second round of analysis. The inventory driver also had two indicators with outer factor loading less than 0.7, including Inv 1 and 3. Inv 3 had the lowest factor loading value in this driver with 0.112. Hence, Inv 3 was nominated to be removed from the construct in the second round of analysis. The location driver had shown two indicators with outer factor loading less than 0.7, including Loc 2 and 3. In this case, the factor loadings of both items were very close. Therefore, they were kept in the construct for the second round of analysis.

The production driver also had three indicators with outer factor loading less than 0.7, including Pro 2, 3, and 5. In this case, factor loadings of all items were very close to each other. Therefore, they were kept in the construct for the second round of analysis. The transportation driver had one indicator with outer factor loading less than 0.7 named Trans2. In this case, the factor loading of Trans2 was the lowest value, and its Cronbach's Alpha was lower than 0.7. Therefore, it was nominated to be removed from the construct in the second round of analysis to enhance the reliability of the construct. The TSCV had one indicator with outer factor loading less than 0.7, including TSCV3 (0.250). In this case, the factor loading of TSCV3 was not significantly low enough to be removed from the construct. Therefore, it was kept in the construct for the second round of analysis.

Table 5-1-First round of confirmatory factor analysis (CFA) process. Factor loading of the initial construct.

	DPP	Information	Inventory	Location	Production	TSCV	Transportation
DPP1	0.324						
DPP2	0.836						
DPP3	0.862						
DPP4	0.083						
DPP5	0.235						
DPP6	0.809						
DPP7	0.923						
DPP8	0.374						
Inf1		0.900					
Inf2		0.384					
Inf3		0.870					
Inf4		0.171					
Inf5		0.135					
Inf6		0.457					
Inf7		0.865					
Inf8		0.902					
Inf9		0.335					
Inv1			0.262				
Inv2			0.899				
Inv3			0.112				

Inv4			0.820				
Inv5			0.920				
Inv6			0.936				
Loc1				0.925			
Loc2				0.378			
Loc3				0.258			
Loc4				0.919			
Loc5				0.935			
Pro1					0.907		
Pro2					0.268		
Pro3					0.344		
Pro4					0.834		
Pro5					0.425		
Pro6					0.900		
Pro7					0.925		
Tran1							0.905
Tran2							0.240
Tran3							0.883
Tscv1						0.955	
Tscv2						0.929	
Tscv3						0.250	
Tscv4						0.942	

Table 5-2 shows the initial construct's quality criteria, including five SC drivers, DPP, and TSCV. The transportation driver had Cronbach's Alpha lower than 0.7 and DPP, and the information driver had AVE lower than 0.5. Hence, nominated items from DPP, transportation, and information variables can be removed to enhance the construct's reliability and internal consistency in the second round of analysis.

Table 5-2-First round of confirmatory factor analysis (CFA) process. Quality criteria of the initial construct.			
	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
DPP	0.740	0.806	0.407
Information	0.774	0.825	0.405
Inventory	0.777	0.852	0.547
Location	0.756	0.840	0.556
Production	0.804	0.860	0.508
TSCV	0.802	0.881	0.681
Transportation	0.544	0.754	0.552

5.2.2 CFA Round 1- Bootstrapping of initial construct

Figure 5-2 shows the initial construct's bootstrapping test, including five SC drivers, DPP, and TSCV variables with their indicators. The yellow rectangle indicates the indicators in this analysis, and the blue circle shows the factors or variables. For the weighting scheme, the factor option was selected in SmartPLS software. The numbers shown represent the path coefficient and T-value between factors and indicators and between two factors. Several indicators had T-values between |±1.96| including Inf 4, Inf 5, Inv3, Tran 2, and DPP 4. Hence, these factors were shortlisted for removal.

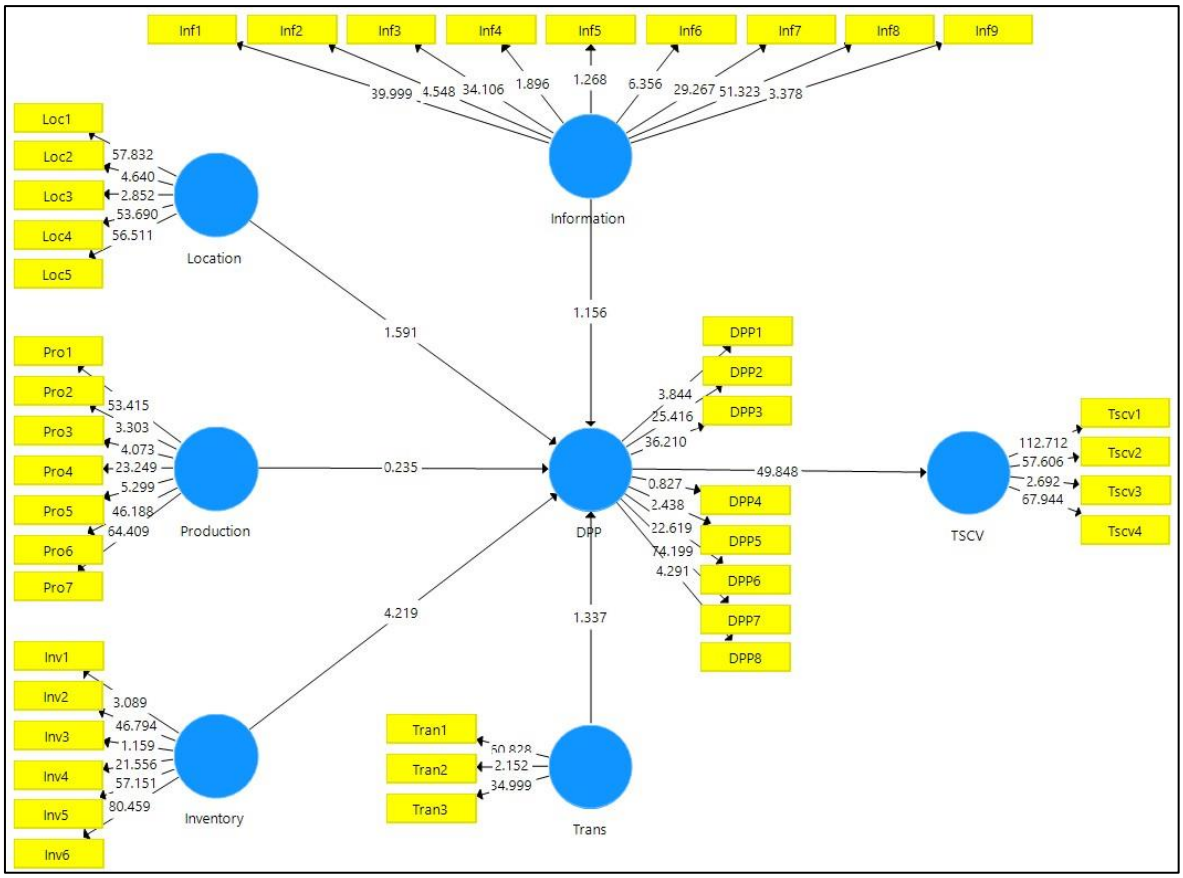


Figure 5-2-First round of bootstrapping test for an initial structural model of SC drivers.

Table 5-3 shows the results of the first round of bootstrapping tests for the initial construct to identify T-values of indicators. The shortlisted items, including Inf 4, Inf 5, Inv 3, Tran 2, and DPP 4, had the lowest factor loadings ($O \leq 0.7$) and T-statistics lower than the threshold limit ($|\pm 1.96|$) which can be removed from the construct in the next round of analysis. Considering the PLS test in the previous stage and the current bootstrapping test, these factors suggested withdrawing from the construct, including Inf 2, Inf 4, Inf 5, Inf 6, DPP 1, DPP 4, DPP 5, DPP 8, and Tran 2.

Table 5-3-First round of bootstrapping test of the initial construct to identify T-values of indicators.

	Factor Loading (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
DPP4 <- DPP	0.083	0.082	0.101	0.827	0.408
Inv3 <- Inventory	0.112	0.111	0.097	1.159	0.247

Inf5 <- Information	0.135	0.130	0.106	1.268	0.205
Inf4 <- Information	0.171	0.168	0.090	1.896	0.058
DPP5 <- DPP	0.235	0.232	0.096	2.438	0.015
Tran2 <- Trans	0.240	0.236	0.112	2.152	0.031
Tscv3 <- TSCV	0.250	0.247	0.093	2.692	0.007
Loc3 <- Location	0.258	0.256	0.090	2.852	0.004
Inv1 <- Inventory	0.262	0.260	0.085	3.089	0.002
Pro2 <- Production	0.268	0.265	0.081	3.303	0.001
DPP1 <- DPP	0.324	0.322	0.084	3.844	0.000
Inf9 <- Information	0.335	0.329	0.099	3.378	0.001
Pro3 <- Production	0.344	0.340	0.084	4.073	0.000
DPP8 <- DPP	0.374	0.373	0.087	4.291	0.000
Loc2 <- Location	0.378	0.375	0.081	4.640	0.000
Inf2 <- Information	0.384	0.381	0.084	4.548	0.000
Pro5 <- Production	0.425	0.421	0.080	5.299	0.000
Inf6 <- Information	0.457	0.454	0.072	6.356	0.000
DPP6 <- DPP	0.809	0.807	0.036	22.619	0.000
Inv4 <- Inventory	0.820	0.818	0.038	21.556	0.000
Pro4 <- Production	0.834	0.832	0.036	23.249	0.000
DPP2 <- DPP	0.836	0.834	0.033	25.416	0.000
DPP3 <- DPP	0.862	0.862	0.024	36.210	0.000
Inf7 <- Information	0.865	0.863	0.030	29.267	0.000
Inf3 <- Information	0.870	0.870	0.026	34.106	0.000
Tran3 <- Trans	0.883	0.881	0.025	34.999	0.000
Inv2 <- Inventory	0.899	0.898	0.019	46.794	0.000
Inf1 <- Information	0.900	0.899	0.022	39.999	0.000
Pro6 <- Production	0.900	0.900	0.019	46.188	0.000
Inf8 <- Information	0.902	0.902	0.018	51.323	0.000
Tran1 <- Trans	0.905	0.904	0.015	60.828	0.000
Pro1 <- Production	0.907	0.907	0.017	53.415	0.000
Loc4 <- Location	0.919	0.918	0.017	53.690	0.000
Inv5 <- Inventory	0.920	0.920	0.016	57.151	0.000
DPP7 <- DPP	0.923	0.922	0.012	74.199	0
Loc1 <- Location	0.925	0.924	0.016	57.832	0.000
Pro7 <- Production	0.925	0.925	0.014	64.409	0.000

Tscv2 <- TSCV	0.929	0.929	0.016	57.606	0.000
Loc5 <- Location	0.935	0.934	0.017	56.511	0.000
Inv6 <- Inventory	0.936	0.936	0.012	80.459	0.000
Tscv4 <- TSCV	0.942	0.941	0.014	67.944	0.000
Tscv1 <- TSCV	0.955	0.955	0.008	112.712	0.000

Table 5-4 demonstrates the results of bootstrapping test of the initial construct to determine the T- statistics (T-values) of pathways between two factors or variables.

According to Hayes & Rockwood (2017), zero must not include between the lower limit confidence interval (LLCI) and the upper limit confidence interval (ULCI) at a 95% confidence interval to accept T-values and factor loadings. Four paths between two variables had the T-values lower than the threshold limit (|±1.96|) at the P-value of 0.05. Therefore, the validity of the construct can be enhanced by omitting the indicators of those variables, which has been performed in the next round of analysis.

Table 5-4-Bootstrapping test of the initial construct to identify T-values of paths between two factors.

	Factor Loading (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	LLCI (2.5%)	ULCI (97.5%)
DPP -> TSCV	0.907	0.908	0.018	49.848	0	0.869	0.94
Information -> DPP	0.134	0.134	0.116	1.156	0.248	-0.091	0.366
Inventory -> DPP	0.559	0.555	0.133	4.219	0	0.286	0.812
Location -> DPP	0.203	0.199	0.128	1.591	0.112	-0.069	0.433
Production -> DPP	-0.034	-0.026	0.145	0.235	0.814	-0.306	0.264
Transportation -> DPP	0.093	0.094	0.07	1.337	0.181	-0.035	0.238

5.2.3 CFA Round 2 – PLS study

In this section, the proposed items (indicators) from the previous round have been removed from the construct, including Inf 2, Inf 4, Inf 5, Inf 6, DPP 1, DPP 4, DPP 5, DPP 8, and Tran 2. Indeed, the second round of the PLS test has been conducted in this section without considering the items mentioned above. Figure 5-3 shows the results of the second round of the PLS algorithm test in the absence of Inf 2, Inf 4, Inf 5, Inf 6, DPP 1, DPP 4, DPP 5, DPP

8, and Tran 2. The factor loading of some factors is enhanced in the absence of the items mentioned above. For instance, in the first round, Inf 3 had the outer loading of 0.870, while by omitting Inf 2, Inf 4, Inf 5, and Inf 6, the outer loading was enhanced to the value of 0.888. Likewise, in the second round, the outer loading of DPP2 increased from 0.836 to 0.860 in the absence of DPP 1, DPP 4, DPP 5, and DPP 8.

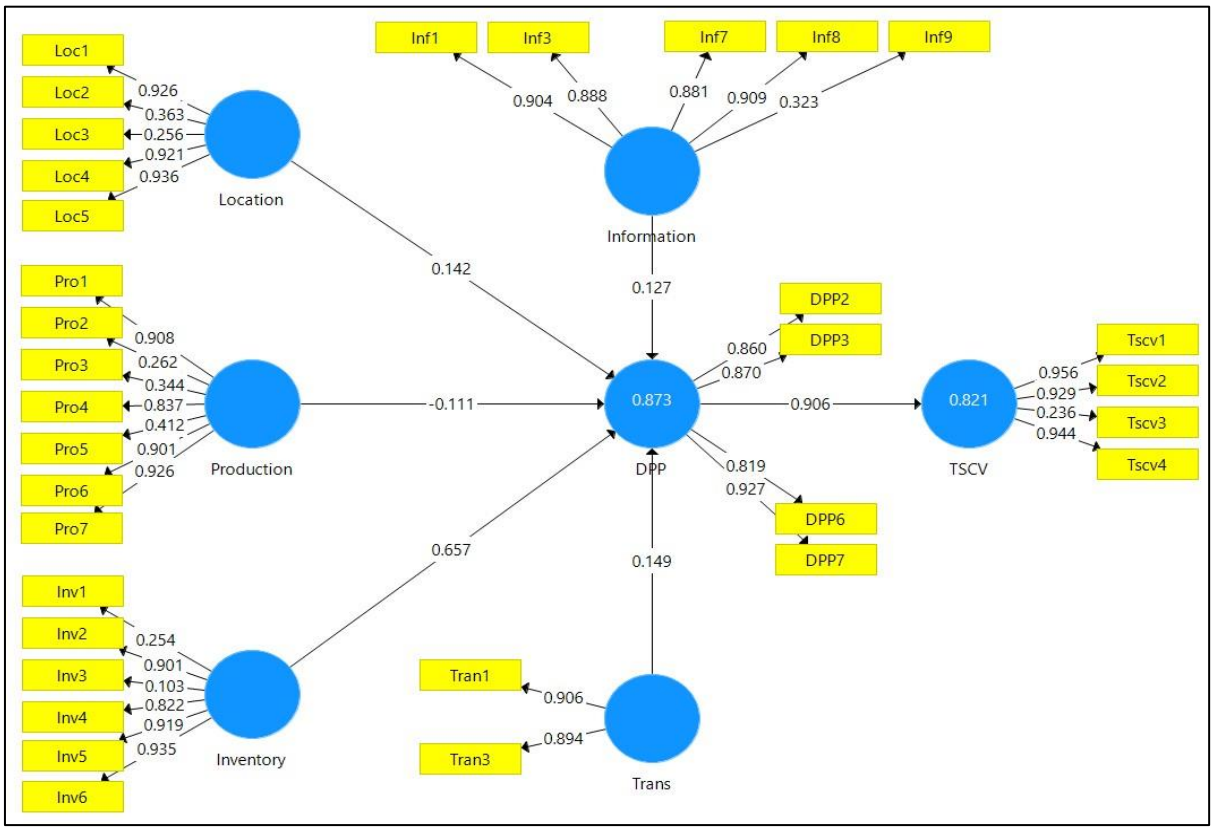


Figure 5-3- Second round of confirmatory factor analysis (CFA) using PLS approach for the second structural model of SC drivers.

At the end of the 2nd round of the PLS test, the outer weight of some items was still lower than the threshold limit (0.7). Table 5-5 lists the factor loading of all items. Thus, the items with a lower threshold limit were highlighted in red. Inf 9, Inv 1, Inv 3, Loc 2, Loc 3, Pro 2, Pro 3, Pro 5, and TSCV 3 have had a factor loading lower than 0.7; they can be shortlisted to be removed from the construct in the third round of PLS analysis.

Table 5-5-Second round of confirmatory factor analysis (CFA) process. PLS of the second construct to identify factor loading of indicators.

	DPP	Information	Inventory	Location	Production	TSCV	Transportation
DPP2	0.860						
DPP3	0.870						
DPP6	0.819						
DPP7	0.927						
Inf1		0.904					
Inf3		0.888					
Inf7		0.881					
Inf8		0.909					
Inf9		0.323					
Inv1			0.254				
Inv2			0.901				
Inv3			0.103				
Inv4			0.822				
Inv5			0.919				
Inv6			0.935				
Loc1				0.926			
Loc2				0.363			
Loc3				0.256			
Loc4				0.921			
Loc5				0.936			
Pro1					0.908		
Pro2					0.262		
Pro3					0.344		
Pro4					0.837		
Pro5					0.412		
Pro6					0.901		
Pro7					0.926		
Tran1							0.906
Tran3							0.894

Tscv1						0.956	
Tscv2						0.929	
Tscv3						0.236	
Tscv4						0.944	

Table 5-6 shows the quality of criteria of the 2nd round of the construct in the absence of the Inf 2, Inf 4, Inf 5, Inf 6, DPP 1, DPP 4, DPP 5, DPP 8, and Tran 2. The AVE for the DPP variable and information driver has improved significantly from 0.407 and 0.405 to 0.756 and 0.662, respectively. In addition, the Cronbach's Alpha of transportation driver was enhanced from 0.544 to 0.765 after removing Tran 2. These improvements were shown that removing items from the first construct improved the quality criteria of the construct.

Table 5-6-Second round of confirmatory factor analysis (CFA) process. Quality Criteria of the second structural model.

	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
DPP	0.892	0.925	0.756
Information	0.851	0.90	0.662
Inventory	0.777	0.851	0.547
Location	0.756	0.839	0.556
Production	0.804	0.859	0.507
TSCV	0.802	0.88	0.681
Transportation	0.765	0.895	0.81

5.2.4 CFA Round 2 – Bootstrapping of structural model 2

Figure 5-4 shows the bootstrapping test of the 2nd construct, including five SC drivers, DPP, and TSCV variables with their indicators. The factor option was selected in SmartPLS V3 software for the weighting scheme. The numbers represented the path coefficient and T-value between factors and indicators and the path coefficient (T-value) between two factors. There are not any indicators with a T-value between the threshold limit$|\pm 1.96|$. Hence, the obtained results of bootstrapping test proved that the shortlisted factors in the first round had been correctly removed from the construct to enhance its reliability and validity.

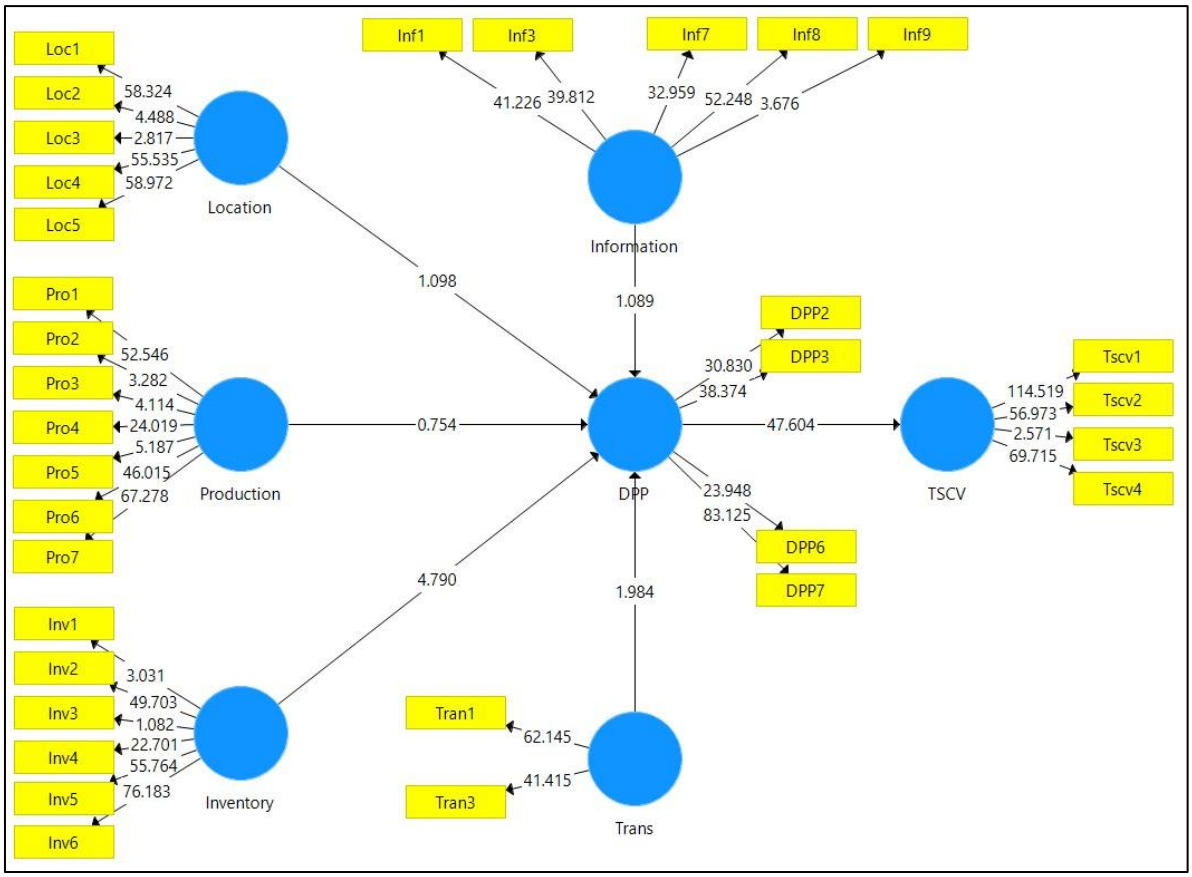


Figure 5-4- the 2nd round of bootstrapping test for the second structural model of SC drivers.

Table 5-7 shows the bootstrapping analysis of the 2nd round, including five SC drivers, DPP, and TSCV variables with their indicators after removing several items, including Inf 2, Inf 4, Inf 5, Inf 6, DPP 1, DPP 4, DPP 5, DPP 8, and Tran 2. Most factor loading and T-values are higher than their assigned thresholds except for Inv 3. Inv 3 has been shortlisted in the PLS analysis concerning its factor loading (0.103). The current analysis observed that its T-Value was lower than 1.96, and its P-value was higher than 0.05. In addition, its factor loadings were lower than 0.7. Therefore, considering the CFA approach, these items should be removed from the final construct.

The results showed that the shortlisted indicators (Inf 9, Inv1, Inv3, Loc2, Loc3, Pro2, Pro3, Pro5, and TSCV 3) must be removed from the construct in the third round of analyses (final round).

Table 5-7-Second round of confirmatory factor analysis (CFA) process. Bootstrapping of the second structural model to identify t -values of indicators.

	Factor Loading (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
DPP2 <- DPP	0.86	0.859	0.028	30.83	0
DPP3 <- DPP	0.87	0.87	0.023	38.374	0
DPP6 <- DPP	0.819	0.817	0.034	23.948	0
DPP7 <- DPP	0.927	0.927	0.011	83.125	0
Inf1 <- Information	0.904	0.904	0.022	41.226	0
Inf3 <- Information	0.888	0.888	0.022	39.812	0
Inf7 <- Information	0.881	0.88	0.027	32.959	0
Inf8 <- Information	0.909	0.909	0.017	52.248	0
Inf9 <- Information	0.323	0.32	0.088	3.676	0
Inv1 <- Inventory	0.254	0.253	0.084	3.031	0.002
Inv2 <- Inventory	0.901	0.9	0.018	49.703	0
Inv3 <- Inventory	0.103	0.1	0.095	1.082	0.279
Inv4 <- Inventory	0.822	0.82	0.036	22.701	0
Inv5 <- Inventory	0.919	0.919	0.016	55.764	0
Inv6 <- Inventory	0.935	0.935	0.012	76.183	0
Loc1 <- Location	0.926	0.925	0.016	58.324	0
Loc2 <- Location	0.363	0.359	0.081	4.488	0
Loc3 <- Location	0.256	0.253	0.091	2.817	0.005
Loc4 <- Location	0.921	0.92	0.017	55.535	0
Loc5 <- Location	0.936	0.935	0.016	58.972	0
Pro1 <- Production	0.908	0.907	0.017	52.546	0
Pro2 <- Production	0.262	0.258	0.08	3.282	0.001
Pro3 <- Production	0.344	0.341	0.084	4.114	0
Pro4 <- Production	0.837	0.835	0.035	24.019	0
Pro5 <- Production	0.412	0.408	0.079	5.187	0
Pro6 <- Production	0.901	0.9	0.02	46.015	0
Pro7 <- Production	0.926	0.926	0.014	67.278	0
Tran1 <- Trans	0.906	0.906	0.015	62.145	0

Tran3 <- Trans	0.894	0.893	0.022	41.415	0
Tscv1 <- TSCV	0.956	0.956	0.008	114.519	0
Tscv2 <- TSCV	0.929	0.928	0.016	56.973	0
Tscv3 <- TSCV	0.236	0.234	0.092	2.571	0.01
Tscv4 <- TSCV	0.944	0.943	0.014	69.715	0

5.2.5 CFA Round 3 – PLS study of the final construct

In the 3rd round of CFA analysis, the proposed items (indicators) from the previous round have been removed from the construct. The 3rd round of the PLS test has been conducted in this section without considering the abovementioned indicators. Figure 5-5 shows the results of the final round of the PLS algorithm test in the absence of the Inf 2, Inf 4, Inf 5, Inf 6, DPP 1, DPP 4, DPP 5, DPP 8, Tran 2, Inv 1, Inv 3, Loc 2, Loc 3, Pro 2, Pro 3, Pro 5, and TSCV 3. The factor loading of all indicators was above the assigned threshold (0.7) in the absence of the items mentioned above.

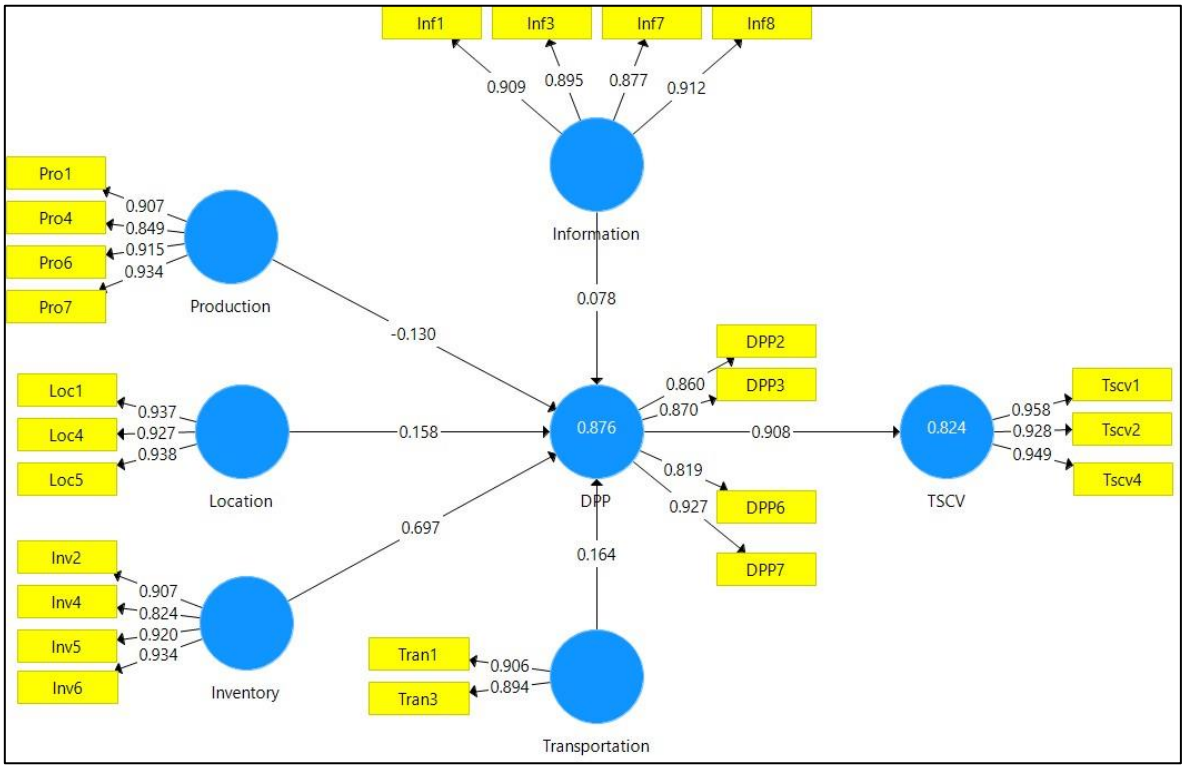


Figure 5-5-Third round of confirmatory factor analysis (CFA) using PLS approach for the final structural model of SC drivers.

Table 5-8 shows indicators' factor loading after conducting three PLS test rounds. It can be concluded that the factor loading of all items was improved. Whereas merely two indicators remained in the construct for the transportation driver. The single factor with two indicators has two error variances and two loadings that create four parameters to estimate, resulting in three non-trivial entries remaining in the variance-covariance matrix. Therefore, there is insufficient information to evaluate the parameters (Bollen and Long 1993). In addition, Hair et al. (2017) also emphasised that it is essential to have at least three items or indicators per variable to precisely identify the variable. Three items in a single factor will create three error variances, loadings, variance-covariance matrix, and six entries. So, the model is algebraically identified, and the matrix entries can estimate the parameters.

Therefore, considering that only two items remained in the transportation driver, this factor was permanently removed from the construct for further SEM analysis.

Table 5-8-Third round of Confirmatory factor analysis (CFA) process. Factor loading of the third (final) structural model.

	DPP	Information	Inventory	Location	Production	TSCV	Transportation
DPP2	0.860						
DPP3	0.87						
DPP6	0.819						
DPP7	0.927						
Inf1		0.909					
Inf3		0.895					
Inf7		0.877					
Inf8		0.912					
Inv2			0.907				
Inv4			0.824				
Inv5			0.92				
Inv6			0.934				
Loc1				0.937			
Loc4				0.927			
Loc5				0.938			
Pro1					0.907		
Pro4					0.849		

Pro6					0.915		
Pro7					0.934		
Tran1							0.906
Tran3							0.894
Tscv1						0.958	
Tscv2						0.928	
Tscv4						0.949	
*: The transportation factor has been removed from the final construct due to the remaining two measures (indicators) in the factor and cause creating a negative degree of freedom.							

Table 5-9 shows the quality criteria of the final construct after removing the following items, including Inf 9, Inf 2, Inf 4, Inf 5, Inf 6, DPP 1, DPP 4, DPP 5, DPP 8, Tran 2, Inv 1, Inv 3, Loc 2, Loc 3, Pro 2, Pro 3, Pro 5, and TSCV 3. The inventory driver's AVE value has improved from 0.546 to 0.805 after omitting Inv 1 and Inv 3 from the construct. Also, for the inventory driver, the value of Cronbach's Alpha and CR were enhanced significantly from the 2nd round to the final analysis due to removing two indicators. Likewise, the quality criteria of location, production, and TSCV were improved when comparing the computations in the previous round to the analysis in this section. For instance, for the location driver, the values of Cronbach's Alpha, CR, and AVE were increased by 22.6%, 13.7%, and 57%, respectively, after removing Loc 2 and Loc 3 from the construct. Furthermore, for the production driver and TSCV variable, by comparing the attained results between the 2nd round and 3rd round, it can be stated that the quality criteria for these variables were improved considerably after omitting the items from the construct. Consequently, the obtained result of the conducted CFA in three rounds confirmed that removing the shortlisted items enhanced the reliability and internal consistency of the final construct.

Table 5-9-Third round of confirmatory factor analysis (CFA) process. Quality Criteria of the third (final) structural model.

	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
DPP	0.892	0.925	0.756
Information	0.92	0.944	0.807
Inventory	0.918	0.943	0.805

Location	0.927	0.954	0.873
Production	0.923	0.946	0.814
TSCV	0.94	0.961	0.893
Transportation	0.765	0.895	0.810

5.2.6 CFA Round 3 – Bootstrapping of structural model 3

It is essential to conduct bootstrapping analysis to ensure whether the path analysis between the indicators and variables was not violated. In this section, the bootstrapping analysis was conducted for the third time to observe how the T-statistics (T-value) were affected after omitting the nominated items in the second round. The T-values of all indicators are higher than the assigned threshold limit. Also, it has been observed that the T-value of some items slightly increased after deleting the other items (with lower factor loading) in a variable which shows how the interaction between indicators has affected the statistics values. For instance, in the production driver, after omitting Pro 2, Pro 3, and Pro 5 (due to their lower factor loading), the T-value of Pro 6 and Pro 7 has been increased from 46.015 and 67.278 to 52.359 and 72.326, respectively, at 95% of confidence level. Hence, it can be concluded that the items mentioned above enhanced the T-statistics' value. Figure 5-6 shows the third round of bootstrapping test for the final structural model of SC drivers.

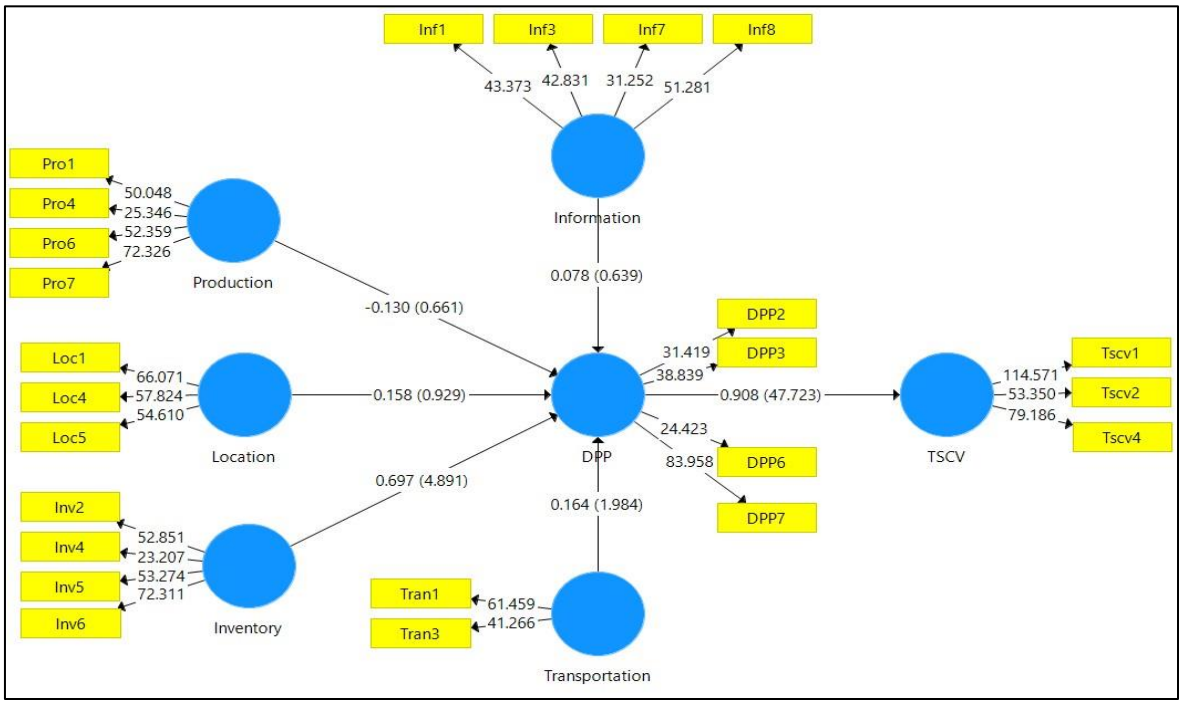


Figure 5-6-Third round of bootstrapping test for the final structural model of SC drivers.

Table 5-10 demonstrates the final construct's T-values and factor loadings of all remaining indicators at a 95% confidence level. All remaining indicators of the final construct have shown an adequate range of T-statistics and factor loadings which were higher than the defined accepted limit. In this case, the discriminant validity of the accepted construct after the final round of CFA was investigated to ensure the internal consistency between the factors was not violated.

Table 5-10-Third round of confirmatory factor analysis (CFA) process. Bootstrapping of the third structural model to identify t-values of indicators.

	Factor Loading (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
DPP2 <- DPP	0.86	0.859	0.027	31.419	0
DPP3 <- DPP	0.87	0.87	0.022	38.839	0
DPP6 <- DPP	0.819	0.817	0.034	24.423	0
DPP7 <- DPP	0.927	0.927	0.011	83.958	0
Inf1 <- Information	0.909	0.908	0.021	43.373	0
Inf3 <- Information	0.895	0.895	0.021	42.831	0
Inf7 <- Information	0.877	0.876	0.028	31.252	0
Inf8 <- Information	0.912	0.911	0.018	51.281	0
Inv2 <- Inventory	0.907	0.907	0.017	52.851	0
Inv4 <- Inventory	0.824	0.822	0.035	23.207	0
Inv5 <- Inventory	0.92	0.919	0.017	53.274	0
Inv6 <- Inventory	0.934	0.934	0.013	72.311	0
Loc1 <- Location	0.937	0.937	0.014	66.071	0
Loc4 <- Location	0.927	0.926	0.016	57.824	0
Loc5 <- Location	0.938	0.937	0.017	54.61	0
Pro1 <- Production	0.907	0.907	0.018	50.048	0
Pro4 <- Production	0.849	0.848	0.034	25.346	0
Pro6 <- Production	0.915	0.915	0.017	52.359	0
Pro7 <- Production	0.934	0.934	0.013	72.326	0
Tran1 <- Transportation	0.906	0.906	0.015	61.459	0
Tran3 <- Transportation	0.894	0.893	0.022	41.266	0

Tscv1 <- TSCV	0.958	0.958	0.008	114.571	0
Tscv2 <- TSCV	0.928	0.927	0.017	53.35	0
Tscv4 <- TSCV	0.949	0.948	0.012	79.186	0

As discussed in chapter 3, for this thesis, the Fornell-Larcker criterion has been applied to check the discriminant validity of the approved construct after removing the items from the construct and obtaining the final construct. Table 5-11 shows the acquired discriminant validity results based on the Fornell-Larcker criterion of the final structural model. All values in the diagonal of the matrix have had the highest values compared with the off-diagonal values, which shows that each variable had the highest correlation with itself rather than other variables. In other words, the measures of the developed construct have not been significantly related. They had not repeated each other, and there was no overlapping measurement. Therefore, the discriminant validity has been accepted for this measurement model.

Table 5-11-Discriminant Validity based on Fornell-Larcker criterion of the final structural model

	DPP	Information	Inventory	Location	Production	TSCV	Transportation
DPP	0.870						
Information	0.801	0.898					
Inventory	0.830	0.846	0.897				
Location	0.863	0.825	0.845	0.934			
Production	0.858	0.831	0.839	0.856	0.902		
TSCV	0.808	0.822	0.831	0.933	0.834	0.945	
Transportation	0.810	0.852	0.814	0.787	0.857	0.766	0.900

5.3 CFA of Moderator Factors

The main effect presents the simple relation between two variables in which a single independent variable has affected the dependent variable. In the presence of an interaction effect, a researcher can analyse the existing relationships between the variables rather than consider a simple analysis between two variables (Krantz 2019).

In this study, the PLS and bootstrapping analyses have been conducted in the presence of three continuous moderators, including basis & foundation, market, and business & enterprise, using SmartPLS software. The two-stage approach has been used as a default technique for the main hypotheses 3, 4, and 5. However, the productivity approach has also been tested for

three main moderation effects to ensure that the main hypotheses have been accepted using two approaches. Within the CFA approach, two rounds of PLS and bootstrapping tests were applied for the moderators to reduce the number of indicators for each moderator. This stage requires developing the construct associated with the accepted indicators of four SC drivers (note: transportation driver was removed from the construct) and taking indicators of DPP. In this case, all accepted indicators from four SC drivers were inserted into one driver named a supply chain driver in the presence of three moderators, including basis & foundation, market, and business & enterprise. The PLS and bootstrapping tests were applied for each round of analysis to determine the outer weight of factor loading for the indicators of the moderators. In addition, the quality criteria, including Cronbach's Alpha, CR, and AVE, were assessed after the PLS algorithm test. The discriminant validity based on the Fornell-Larcker criterion was deployed after the final bootstrapping test of the accepted construct.

The obtained results were reported in two different approaches, including the graphical representation and tabular, to ensure that all details were included and the quality of the outcomes was not violated.

5.3.1 CFA Round 1 – PLS of initial construct included moderators

Figure 5-7 shows an initial construct including all accepted SC driver indicators, obtained DPP indicators, and all indicators belonging to three moderators. The initial construct included 15 SC indicators in one driver, four indicators of DPP, nine indicators of basis & foundation, eight indicators of the market, and eight indicators of business & enterprise.

The results of the first round of PLS analysis show that all SC indicators and indicators of DPP have had factor loading higher than the threshold limit (0.7). The factor loadings of some indicators belonging to the moderators were lower than the accepted limit, which would be removed from the construct to enhance the reliability and internal consistency.

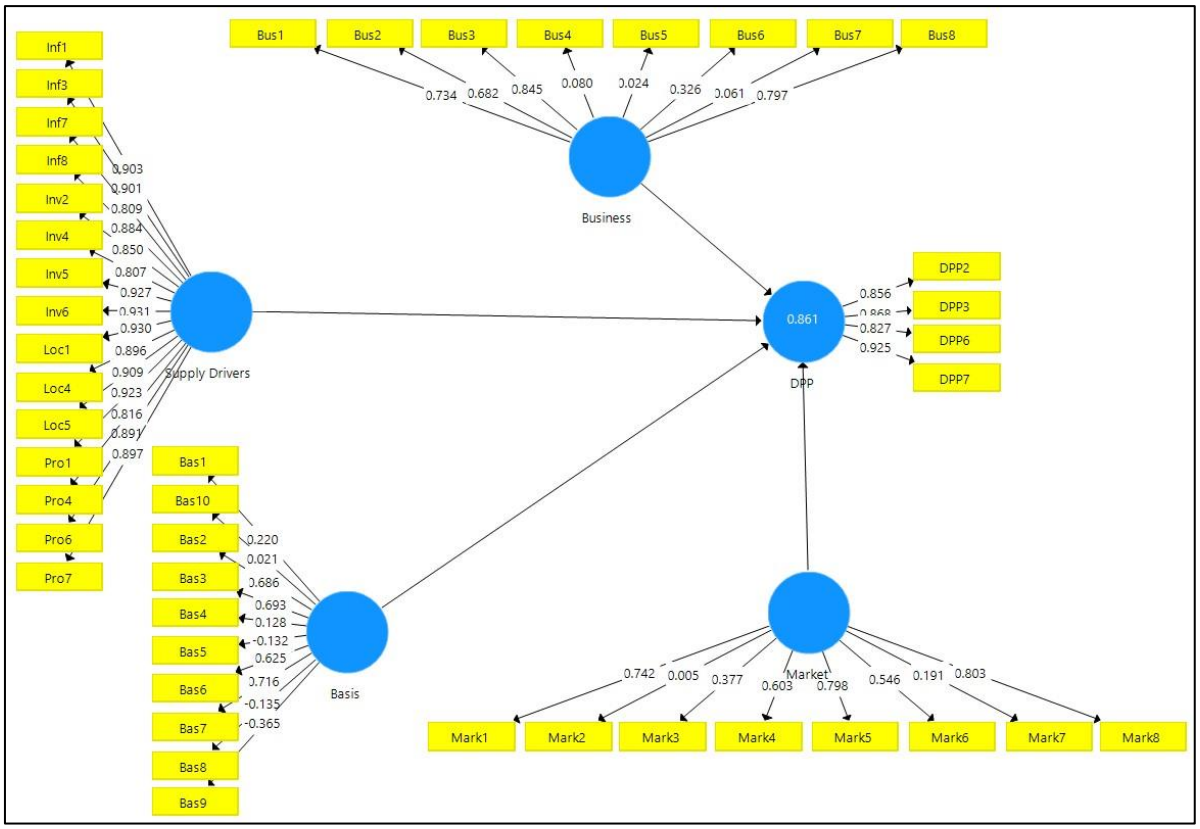


Figure 5-7-First round of confirmatory factor analysis (CFA) using PLS approach for an initial structural model of moderators. Effect of moderators between supply drivers and DPP.

Table 5-12 shows the obtained results from the initial construct after performing the PLS test. Several indicators of moderators have had an outer weight of factor loadings lower than the accepted limit (0.7). In this case, all items of the basis & foundation, four items of the market moderator (Mark 2, Mark 3, Mark 6, and Mark 7), and four indicators of business & enterprise (Bus 4, Bus 5, Bus 6, and Bus 7) have had factor loadings lower than the threshold limit. These items were nominated to be removed from the construct after studying the quality criteria of the initial construct.

Table 5-12-Initial structural model of moderators. Using PLS analysis to identify the factor loading of moderators.

	Basis	Business	DPP	Market	Supply Drivers
Bas1	0.22				
Bas10	0.021				
Bas2	0.686				

Bas3	0.693				
Bas4	0.128				
Bas5	-0.132				
Bas6	0.625				
Bas7	0.716				
Bas8	-0.135				
Bas9	-0.365				
Bus1		0.734			
Bus2		0.682			
Bus3		0.845			
Bus4		0.08			
Bus5		0.024			
Bus6		0.326			
Bus7		0.061			
Bus8		0.797			
DPP2			0.856		
DPP3			0.868		
DPP6			0.827		
DPP7			0.925		
Inf1					0.903
Inf3					0.901
Inf7					0.809
Inf8					0.884
Inv2					0.85
Inv4					0.807
Inv5					0.927
Inv6					0.931
Loc1					0.93
Loc4					0.896
Loc5					0.909
Mark1				0.742	
Mark2				0.005	

Mark3				0.377	
Mark4				0.603	
Mark5				0.798	
Mark6				0.546	
Mark7				0.191	
Mark8				0.803	
Pro1					0.923
Pro4					0.816
Pro6					0.891
Pro7					0.897

Table 5-13 shows the quality criteria of the initial construct in the presence of the moderators, including Cronbach's Alpha, CR, and AVE. Although the Cronbach's Alpha and CR of the variables were higher than the threshold limit (≥ 0.7), the AVE values of the moderators were lower than the accepted limit (≤ 0.5). The AVE values for basis & foundation, market and business & enterprise were reported as 0.157, 0.308, and 0.334, respectively. Hence, it is permitted to remove the shortlisted indicators (i.e., highlighted indicators in the previous section) from the model to enhance the reliability and internal consistency of the construct.
On the other hand, all quality criteria of the SC driver and DPP variable were higher than the assigned threshold limit, demonstrating no need to omit any items from the variables.

Table 5-13-Quality criteria of the initial structural model of moderators.

	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Basis (Moderator 1)	0.451	0.433	0.209
Market (Moderator 2)	0.681	0.695	0.309
DPP	0.892	0.925	0.756
Business (Moderator 3)	0.721	0.756	0.334
Supply Drivers	0.98	0.982	0.785

5.3.2 CFA Round 1– Bootstrapping test of the initial construct with moderators

It is essential to conduct bootstrapping analysis to ensure whether the path analysis between variables and their indicators was not violated. In this section, the bootstrapping analysis was conducted for the initial construct to observe how the T-statistics (T-value) were altered. Figure 5-8 shows the obtained results of bootstrapping test in the presence of three moderators to observe the T-values of indicators. All indicators of basis, Mark 2, Mark 3, Mark 7, Bus 6, Bus4, Bus5, and Bus7 have had T-statistics lower than |±1.96| at the 95% confidence intervals. Therefore, these indicators must be removed from the construct to enhance the quality criteria of the model.

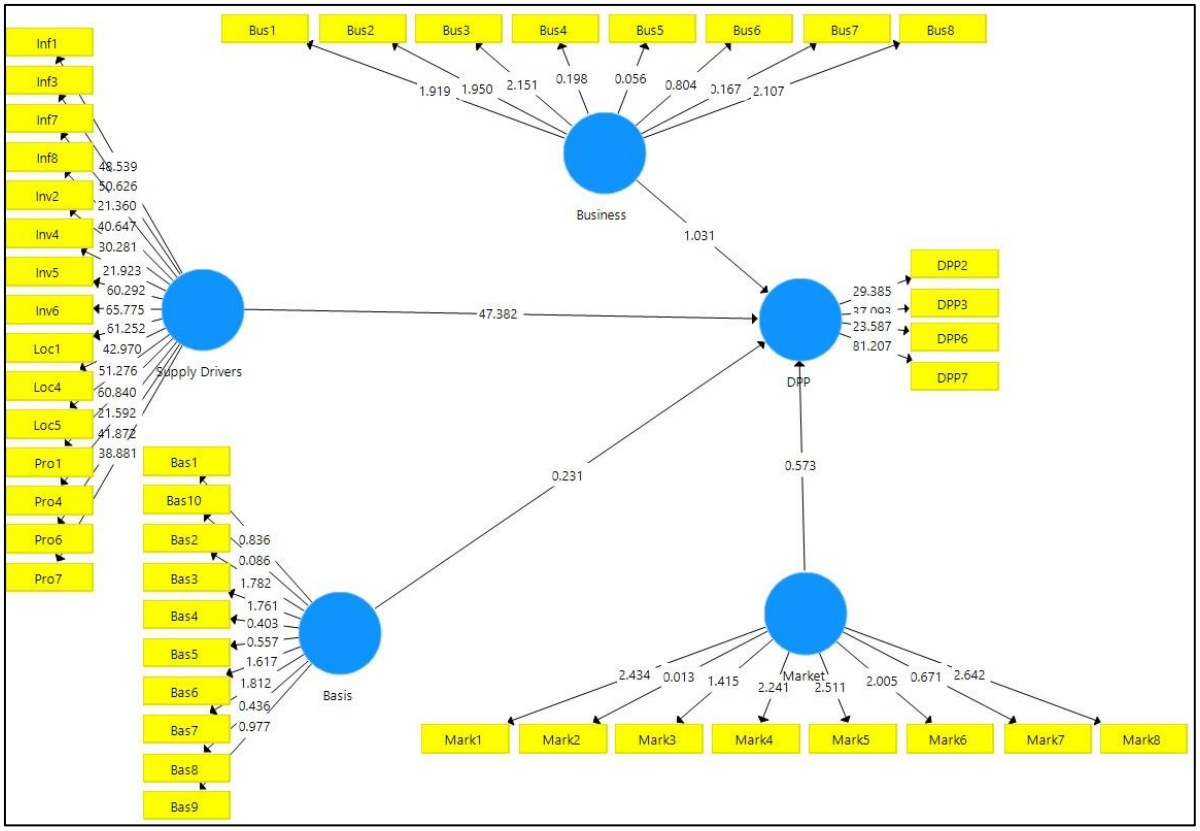


Figure 5-8- Bootstrapping test of initial structural model of moderators. Effect of moderators between supply drivers and DPP.

Table 5-14 shows the results of the first round of bootstrapping tests in the presence of the three moderators, including factor loading and T-value of the indicators. The factor loadings of several items were lower than 0.7, which were highlighted as red.

The indicators that should be removed from the initial model to enhance the construct's reliability were listed as follows; however, eliminating the items started from the minimum values of the factor loadings. In this case, the following items were selected to be removed

from the construct to finalise the last construct Mark 2, Mark 3, Mark 6, Mark 7, Bus 4, Bus 5, Bus 6, Bus 7, Bas 1, Bas 4, Bas 5, Bas 8, Bas 9, and Bas 10. Hence, these items were removed from the construct to conclude the final round of the CFA analysis of the moderators.

Table 5-14-First round of T-statistic of the initial structural model of moderators.

	Factor Loading (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Bas1 <- Basis	0.22	0.108	0.263	0.836	0.403
Bas10 <- Basis	0.021	0.005	0.243	0.086	0.931
Bas2 <- Basis	0.686	0.455	0.385	1.782	0.075
Bas3 <- Basis	0.693	0.496	0.394	1.761	0.078
Bas4 <- Basis	0.128	0.016	0.317	0.403	0.687
Bas5 <- Basis	-0.132	-0.026	0.237	0.557	0.578
Bas6 <- Basis	0.625	0.439	0.386	1.617	0.106
Bas7 <- Basis	0.716	0.487	0.395	1.812	0.07
Bas8 <- Basis	-0.135	0.034	0.309	0.436	0.663
Bas9 <- Basis	-0.365	-0.101	0.373	0.977	0.328
Bus1 <- Business	0.734	0.458	0.382	1.919	0.055
Bus2 <- Business	0.682	0.426	0.35	1.95	0.051
Bus3 <- Business	0.845	0.515	0.393	2.151	0.032
Bus4 <- Business	0.08	0.139	0.402	0.198	0.843
Bus5 <- Business	0.024	0.11	0.422	0.056	0.955
Bus6 <- Business	0.326	0.31	0.406	0.804	0.421
Bus7 <- Business	0.061	0.19	0.365	0.167	0.868
Bus8 <- Business	0.797	0.492	0.378	2.107	0.035
DPP2 <- DPP	0.856	0.856	0.029	29.385	0
DPP3 <- DPP	0.868	0.868	0.023	37.093	0
DPP6 <- DPP	0.827	0.825	0.035	23.587	0
DPP7 <- DPP	0.925	0.926	0.011	81.207	0
Inf1 <- Supply Drivers	0.903	0.903	0.019	48.539	0
Inf3 <- Supply Drivers	0.901	0.901	0.018	50.626	0
Inf7 <- Supply Drivers	0.809	0.808	0.038	21.36	0

Inf8 <- Supply Drivers	0.884	0.884	0.022	40.647	0
Inv2 <- Supply Drivers	0.85	0.851	0.028	30.281	0
Inv4 <- Supply Drivers	0.807	0.806	0.037	21.923	0
Inv5 <- Supply Drivers	0.927	0.927	0.015	60.292	0
Inv6 <- Supply Drivers	0.931	0.931	0.014	65.775	0
Loc1 <- Supply Drivers	0.93	0.93	0.015	61.252	0
Loc4 <- Supply Drivers	0.896	0.896	0.021	42.97	0
Loc5 <- Supply Drivers	0.909	0.909	0.018	51.276	0
Mark1 <- Market	0.742	0.572	0.305	2.434	0.015
Mark2 <- Market	0.005	0.089	0.34	0.013	0.989
Mark3 <- Market	0.377	0.321	0.266	1.415	0.157
Mark4 <- Market	0.603	0.49	0.269	2.241	0.025
Mark5 <- Market	0.798	0.608	0.318	2.511	0.012
Mark6 <- Market	0.546	0.407	0.272	2.005	0.045
Mark7 <- Market	0.191	0.161	0.285	0.671	0.502
Mark8 <- Market	0.803	0.607	0.304	2.642	0.008
Pro1 <- Supply Drivers	0.923	0.923	0.015	60.84	0
Pro4 <- Supply Drivers	0.816	0.816	0.038	21.592	0
Pro6 <- Supply Drivers	0.891	0.891	0.021	41.872	0
Pro7 <- Supply Drivers	0.897	0.897	0.023	38.881	0

5.3.3 CFA Round 2 – PLS test of the final construct with moderators

After conducting the first round of CFA, the following indicators (or measures), including Mark 2, Mark 3, Mark 6, Mark 7, Bus 4, Bus 5, Bus 6, Bus 7, Bas 1, Bas 4, Bas 5, Bas 8, Bas 9, and Bas 10, were removed from construct, and carried out the final round of PLS and bootstrapping analyses. Figure 5-9 shows the final construct after conducting the 2nd round of the PLS test using SmartPLS software (V3). All remaining indicators of the three moderators have had factor loadings higher than the threshold limits. Thereby, the final model of this study has been finalised with approved indicators to perform the SEM approach in the next stage. Figure 5 9 shows confirmatory factor analysis (CFA) of final structural model of moderators. Effect of moderators between supply drivers and DPP has been shown in this figure.

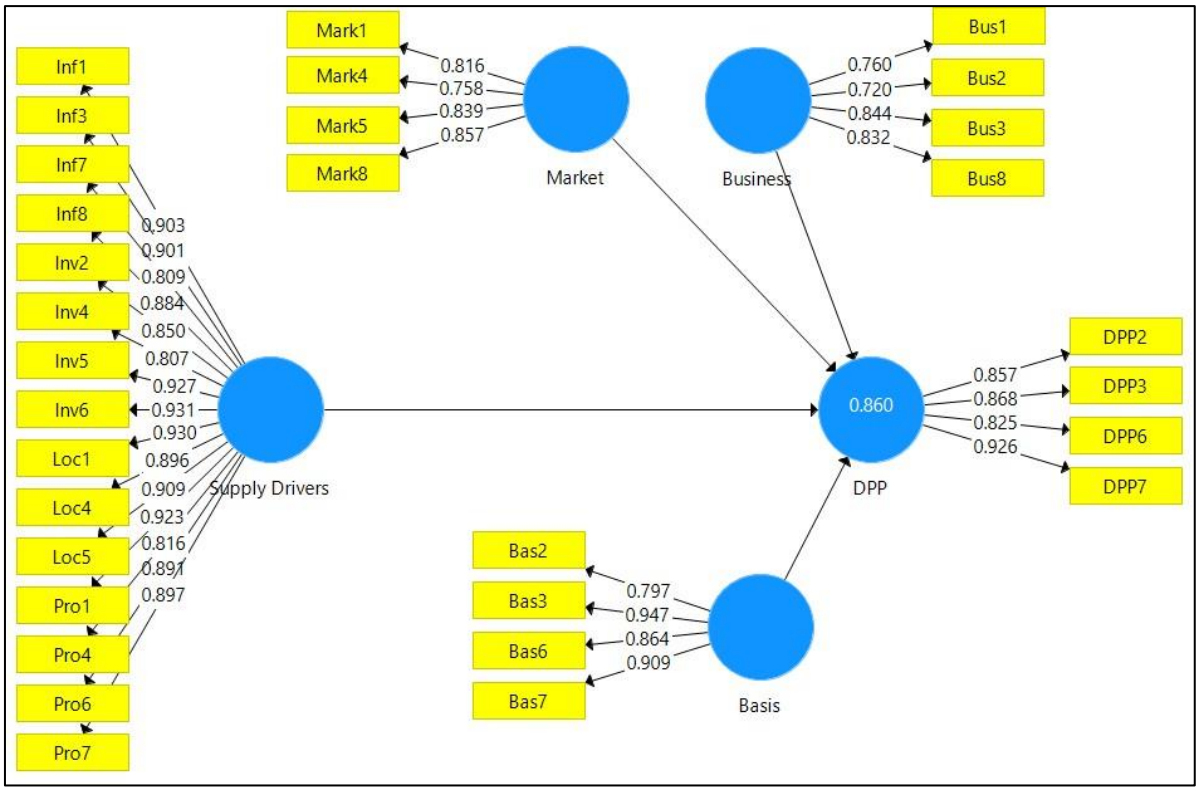


Figure 5-9- Confirmatory factor analysis (CFA) of final structural model of moderators. Effect of moderators between supply drivers and DPP.

Table 5-15 shows the final construct's outer weight of factor loading. The factor loading of all indicators was higher than the threshold limit. Hence, the obtained model consisting of SC drivers and DPP has been finalised in the presence of three moderators to conduct the bootstrapping test in the next stage.

Table 5-15-CFA of the final structural model of moderators. Using PLS analysis to identify the outer weight of factor loading of moderators.

	Basis (Mo 1)	Business (Mo 3)	DPP	Market (Mo 2)	Supply Drivers
Bas2	0.797				
Bas3	0.947				
Bas6	0.864				
Bas7	0.909				
Bus1		0.76			
Bus2		0.72			
Bus3		0.844			

Bus8		0.832			
DPP2			0.857		
DPP3			0.868		
DPP6			0.825		
DPP7			0.926		
Inf1					0.903
Inf3					0.901
Inf7					0.809
Inf8					0.884
Inv2					0.85
Inv4					0.807
Inv5					0.927
Inv6					0.931
Loc1					0.93
Loc4					0.896
Loc5					0.909
Mark1				0.816	
Mark4				0.758	
Mark5				0.839	
Mark8				0.857	
Pro1					0.923
Pro4					0.816
Pro6					0.891
Pro7					0.897

Table 5-16 shows the quality criteria of the final structural model in the presence of three moderators. The AVE value of basis & foundation, market and business & enterprise was reported to be enhanced from 0.209, 0.309, and 0.334 to 0.776, 0.67, and 0.625, respectively. The enhancement of quality criteria shows that omitting the items mentioned above from the initial construct was permitted; however, the bootstrapping test was conducted to ensure whether the T-values of the remaining items were satisfied.

Table 5-16-Quality criteria of the final structural model of moderators.			
	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Basis & Foundation	0.911	0.933	0.776
Business & Enterprise	0.809	0.869	0.625
DPP	0.892	0.925	0.756
Market	0.839	0.89	0.67
Supply Drivers	0.98	0.982	0.785

5.3.4 CFA Round 2 – Bootstrapping test of the final construct with moderators

Figure 5-10 and table 5-17 show the obtained results of 2nd round of bootstrapping test in the presence of three moderators to observe the T-values of indicators. All remaining indicators have had the outer weight of factor loadings and T-values higher than assigned threshold limits at the 95% confidence intervals. Therefore, it can be stated that the developed final construct has been approved to consider the SEM analysis in the next stage.

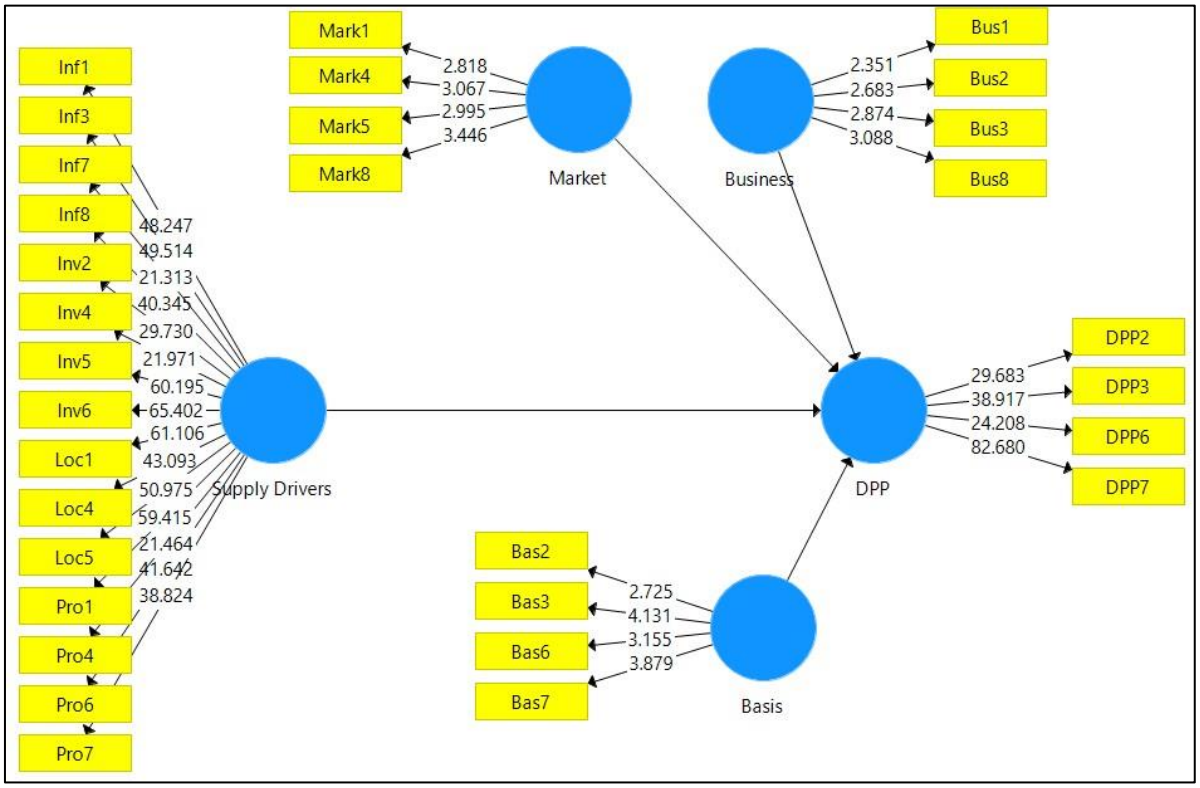


Figure 5-10- T-Statistics of the approved factors related to the final structural model of moderators using bootstrapping approach. Effect of moderators between supply drivers and DPP.

Table 5-17 demonstrates the final construct's T-values and factor loadings of all remaining indicators at a 95% confidence level. All remaining indicators of the final construct have shown an adequate range of T-statistics and factor loadings which were higher than the defined accepted limit. In this case, the discriminant validity of the accepted construct after the final round of CFA was investigated to ensure the internal consistency between the factors was not violated.

Table 5-17- T- Statistics of the final structural model of moderators using the bootstrapping test.

	Factor Loading (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Bas2 <- Basis	0.797	0.732	0.292	2.725	0.006
Bas3 <- Basis	0.947	0.884	0.229	4.131	0
Bas6 <- Basis	0.864	0.794	0.274	3.155	0.002
Bas7 <- Basis	0.909	0.837	0.234	3.879	0
Bus1 <- Business	0.76	0.673	0.323	2.351	0.019
Bus2 <- Business	0.72	0.639	0.268	2.683	0.007
Bus3 <- Business	0.844	0.748	0.294	2.874	0.004
Bus8 <- Business	0.832	0.729	0.269	3.088	0.002
DPP2 <- DPP	0.857	0.857	0.029	29.683	0
DPP3 <- DPP	0.868	0.87	0.022	38.917	0
DPP6 <- DPP	0.825	0.824	0.034	24.208	0
DPP7 <- DPP	0.926	0.926	0.011	82.68	0
Inf1 <- Supply Drivers	0.903	0.903	0.019	48.247	0
Inf3 <- Supply Drivers	0.901	0.901	0.018	49.514	0
Inf7 <- Supply Drivers	0.809	0.809	0.038	21.313	0
Inf8 <- Supply Drivers	0.884	0.885	0.022	40.345	0
Inv2 <- Supply Drivers	0.85	0.851	0.029	29.73	0
Inv4 <- Supply Drivers	0.807	0.806	0.037	21.971	0
Inv5 <- Supply Drivers	0.927	0.927	0.015	60.195	0
Inv6 <- Supply Drivers	0.931	0.931	0.014	65.402	0
Loc1 <- Supply Drivers	0.93	0.93	0.015	61.106	0
Loc4 <- Supply Drivers	0.896	0.897	0.021	43.093	0

Loc5 <- Supply Drivers	0.909	0.909	0.018	50.975	0
Mark1 <- Market	0.816	0.743	0.289	2.818	0.005
Mark4 <- Market	0.758	0.691	0.247	3.067	0.002
Mark5 <- Market	0.839	0.767	0.28	2.995	0.003
Mark8 <- Market	0.857	0.781	0.249	3.446	0.001
Pro1 <- Supply Drivers	0.923	0.923	0.016	59.415	0
Pro4 <- Supply Drivers	0.816	0.816	0.038	21.464	0
Pro6 <- Supply Drivers	0.891	0.891	0.021	41.642	0
Pro7 <- Supply Drivers	0.897	0.897	0.023	38.824	0

Table 5-18 shows the obtained discriminant validity results based on the Fornell-Larcker criterion of the final structural model. All values in the diagonal of the matrix have had the highest values compared to the off-diagonal values, which shows that each variable had the highest correlation with itself rather than other variables. In other words, the measures of the developed construct have not been significantly related. They had not repeated each other, and there was no overlapping measurement. Overall, the discriminant validity has been accepted for this measurement model.

Table 5-18-Discriminant validity of the final structural model of moderators based on the Fornell-Larcker criterion.

	Basis & Foundation	Business & Enterprise	DPP	Market	Supply Drivers
Basis & Foundation	0.881				
Business & Enterprise	0.827	0.791			
DPP	0.096	0.083	0.87		
Market	0.869	0.783	0.084	0.818	
Supply Drivers	0.031	0.009	0.824	0.013	0.886

5.4 Concluding remarks of CFA

At the end of the confirmatory factor analysis of SC drivers and moderators' variables, it was concluded that the four SC drivers and their indicators remained. The transportation driver and its indicators were removed from the construct. Four SC drivers, including information, location, production, and inventory, have remained in the construct, and were inserted into the next round of CFA, which was incorporated with three moderators.

The approved indicators of SC drivers and moderators include the following basis & foundation moderator (Bas 2, Bas 3, Bas 6, and Bas 7), business & enterprise moderator (Bus 1, Bus 2, Bus 3, and Bus 8), market moderator (Mark 1, Mark 4, Mark 5, and Mark 8), DPP (DPP 2, DPP 3, DPP 6, and DPP 7), TSCV (TSCV 1, TSCV 2, and TSCV 4), information variable (Inf 1, Inf 3, Inf 7, and Inf 8), inventory variable (Inv 2, Inv 4, Inv 5, and Inv 6), location deriver (Loc 1, Loc 4, and Loc 5), and production (Pro 1, Pro 4, Pro 6, and Pro 7).

5.5 Path Analysis: Structural Equation Modelling (SEM)

Path analysis, known as structural equation modelling (SEM) or covariance structural equation modelling, is a fundamental method for exploring the relationship and correlation within an assigned construct (Chen et al. 2011). A path coefficient can be interpreted as X changed by one standard deviation, Y will be altered by the "**b** value" of standard deviations, which b is defined as a path coefficient. SmartPLS V3 software applied the ordinary least squares (OLS) regression in a reiterative way to estimate the latent construct scores and partial paths (Hair et al. 2011). In the first step, latent constructs will be produced by a linear combination of standardised variables or outer estimation of variable scores. In this case, SmartPLS V3 software applies a uniform value of 1 as an initial weight for the weights of dependent variables. The software estimates the inner weight for the structural model correlation among latent constructs in the second step. The estimation of inner weights can be applied by selecting one option of weighting scheme from the following options: factor, path, or a centroid weighting scheme. The path weighting scheme was selected for the path analysis using the SmartPLS V3 software (Henseler and Chin 2010).

In the third step, the PLS software estimates the inner approximation of latent construct scores based on the calculated scores from previous steps. Subsequently, the software approximates the outer weights of dependant variables (based on collected scores from the third step) by modifying the initial values of dependant variables, restarting the whole approximation

process at the end of the fourth step. The four stages were repeated until the summation of outer weights' changing between two iterations was lower than a predetermined limit (10^{-7}).

On the other hand, the number of iterations must be predefined and must not be higher than

300. In addition, the subsamples value must be large enough to ensure the stability of results has been satisfied. Hence, the subsamples value for the bootstrapping test was considered 5,000. After the final step, the ultimate path coefficient estimates were determined by applying the ordinary least squares approach for each partial regression in the construct (Henseler and Chin 2010; Hair et al. 2011). The bootstrapping test gives a T-statistic that measures the difference size related to the variation in the collected sample data.

In this study, the bootstrapping test with the option of path analysis was applied to complete path analysis after checking the quality criteria and discriminant validity.

The developed construct of this thesis includes four main hypotheses with 16 sub-hypotheses.

To determine whether the pathway between two variables and the related hypothesis has been supported, the following analyses consist of various studies were conducted:

1- Completing the bootstrapping test via selecting the path item for the weighting scheme.
2- Evaluating the path analysis between two variables (i.e., factors) using bootstrapping analysis ($T - vlaue \geq |\pm 1.96|$ @ $P - value \leq 0.05$)
3- Checking the lower limit confidence interval (LLCI) and the upper limit confidence interval (ULCI) at a 95% confidence interval.
4- Checking the quality criteria of the path or hypothesis (including Cronbach's Alpha ≥ 0.7, composite reliability (CR ≥ 0.7), average variance extracted (AVE ≥ 0.5), and Discriminant Validity based on the Fornell-Larcker criterion).
5- Analysis of R^2 to check the strength of estimation for the proposed model of each hypothesis based on the collected data
6- Determining the supported or unsupported hypotheses.

As discussed, according to (Hayes and Rockwood 2017), the zero must not include the lower limit confidence interval (LLCI) and the upper limit confidence interval (ULCI) at a 95% confidence interval to accept T-values and factor loadings.

5.6 Analysis of Hypothesis 1

The first hypothesis is whether SC drivers cause a change in DPP level in leagile SC. To test the first hypothesis, all approved SC indicators from the CFA stage and approved indicators of DPP obtained from CFA were inserted into the SC driver and DPP variable, respectively. The developed construct of the first hypothesis (H_1) is shown in figure 5-11.

The bootstrapping test was conducted to check the path coefficient and T-statistics between the two variables (i.e., SC driver & DPP) via a 5000-re-sampling procedure. All SC driver and DPP indicators have path coefficients and T-values higher than defined threshold limits of 0.7 and 1.96, respectively. However, the focus of this study was to determine the path coefficient of two main factors, which showed a direct effect between SC driver and DPP due to obtaining a positive correlation. Figure 5-11 indicates that the SC driver- DPP has had a path coefficient of 0.925 @ 95% of confidence intervals, demonstrating higher reliability of the predictive power of the path coefficient. The bootstrap procedure has been used as a hypothesis testing method to calculate the T-value of 5000 re-samplings, allowing testing of the assigned assumption for the construct. The higher T-statistic value shows greater evidence against the null hypothesis. A closer T-value to zero (lower than the absolute of ±1.96) represents no significant difference in standard error units. In other words, a closer T-value to zero shows that there is no adequate evidence to demonstrate an effect between two variables at the predefined confident interval. The performed evaluation shows that the stability of estimates via bootstrapping method was significant, and the first hypothesis is supported.

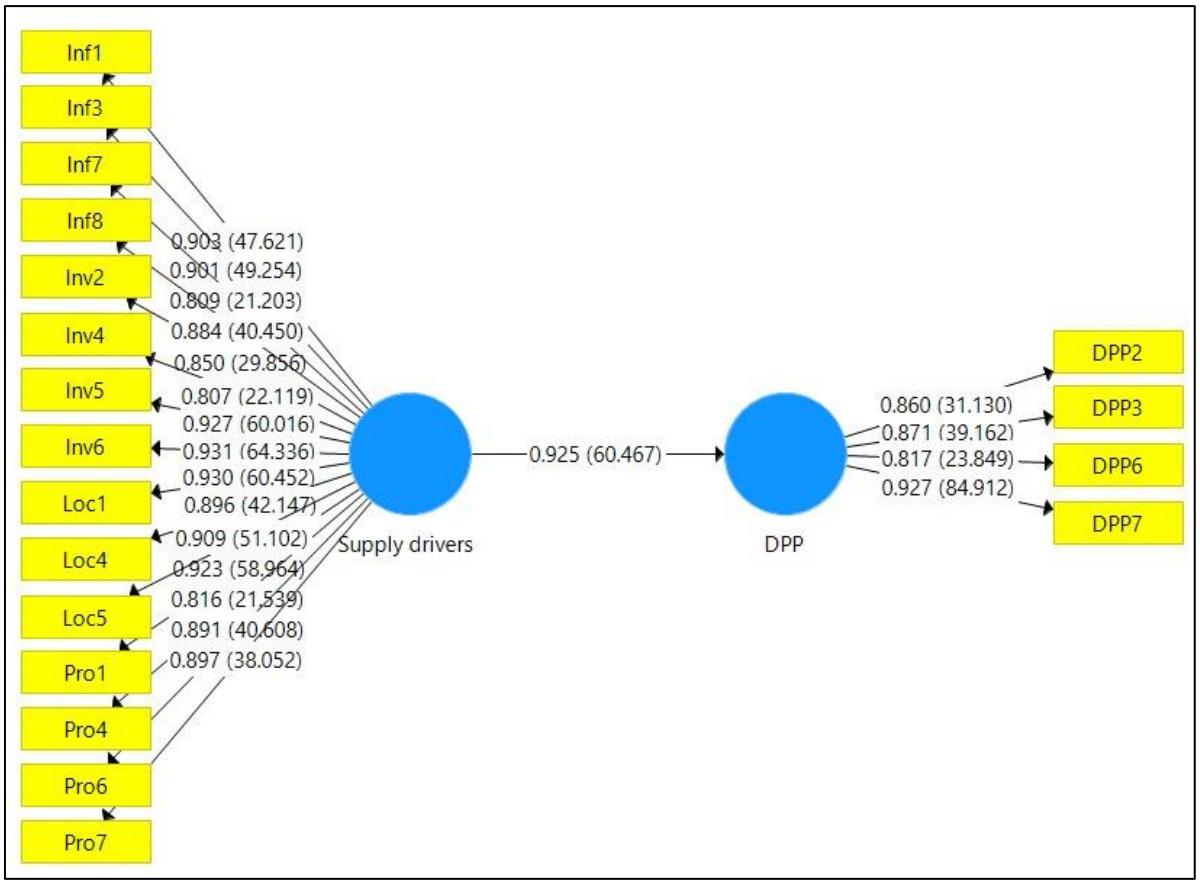


Figure 5-11- Structural equation modelling (SEM) of first hypothesis using path analysis.

Table 5-19 shows the factor loading and T-values of the developed construct related to the first hypothesis's definition. Although it seems this step has been conducted in the CFA section, it is necessary to check the factor loadings and T-values of all approved items by considering the first hypothesis and its construct to ensure the reliability of the study has not been violated. It can be observed that all samples' T-statistics estimate the construct's stability. Furthermore, as expected from the CFA analysis, factor loading of all indicators has had a satisfactory level higher than the threshold limit.

Table 5-19-Hypothesis 1-PLS (factor loading) analysis and bootstrapping (T-Values) calculation

Indicators ← Variable	Factor Loading (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
DPP2 <- DPP	0.86	0.859	0.028	31.13	0
DPP3 <- DPP	0.871	0.871	0.022	39.162	0

DPP6 <- DPP	0.817	0.815	0.034	23.849	0
DPP7 <- DPP	0.927	0.927	0.011	84.912	0
Inf1 <- Supply drivers	0.903	0.902	0.019	47.621	0
Inf3 <- Supply drivers	0.901	0.901	0.018	49.254	0
Inf7 <- Supply drivers	0.809	0.808	0.038	21.203	0
Inf8 <- Supply drivers	0.884	0.884	0.022	40.45	0
Inv2 <- Supply drivers	0.85	0.85	0.028	29.856	0
Inv4 <- Supply drivers	0.807	0.805	0.036	22.119	0
Inv5 <- Supply drivers	0.927	0.927	0.015	60.016	0
Inv6 <- Supply drivers	0.931	0.931	0.014	64.336	0
Loc1 <- Supply drivers	0.93	0.93	0.015	60.452	0
Loc4 <- Supply drivers	0.896	0.896	0.021	42.147	0
Loc5 <- Supply drivers	0.909	0.909	0.018	51.102	0
Pro1 <- Supply drivers	0.923	0.923	0.016	58.964	0
Pro4 <- Supply drivers	0.816	0.815	0.038	21.539	0
Pro6 <- Supply drivers	0.891	0.891	0.022	40.608	0
Pro7 <- Supply drivers	0.897	0.897	0.024	38.052	0

Table 5-20 shows the path coefficient and T-Statistics between two main variables (i.e., SC drivers & DPP) at a 95% confidence level. It can be seen both values are higher than threshold limits, and there is no zero included between the lower and higher limit of confidence intervals. Hence, it can be concluded that the first hypothesis has been approved statistically; however, the quality criteria of the construct have been checked to ensure the reliability and internal consistency of the construct have not been neglected.

Table 5-20-Path analysis of Hypothesis 1

	Path Coefficient (O)	T Statistics (|O/STDEV|)	P Values	LLCI (2.5%)	ULCI (97.5%)	Support (Yes/No)
Supply drivers -> DPP	0.925	0.015	60.467	0.888	0.949	Yes

Table 5-21 demonstrates the first hypothesis's quality criteria, including Cronbach's Alpha, CR, and AVE. It can be observed that all criteria were higher than defined threshold limits which approved that the reliability and internal consistency of the developed construct for the first hypothesis have been certified. Although the R-squared value must not be considered merely to evaluate the fitness of the model but considering the R-squared value alongside the path coefficient and T-value can produce a reasonable prediction about the hypothesis model. R-squared has been computed and reported for DPP as an endogenous variable to determine how the first hypothesis and its developed construct can strongly estimate the variance. Considering the T-Value (60.467) at 95% of intervals level and R-squared value (0.856), it can be concluded that the developed construct for the first hypothesis was fitted to the collected data, and DPP can be explained for 85.6% of the variance.

Table 5-21-Quality criteria of Hypothesis 1- Supply chain drivers cause the change in the positioning of DPP in the leagile supply chain.

	Cronbach's Alpha	CR	AVE	R-squared
DPP	0.892	0.925	0.756	0.856
Supply drivers	0.98	0.982	0.785	--

Table 5-22 shows the discriminant validity based on the Fornell-Larcker criterion of Hypothesis 1. As explained in chapter 3 (i.e., research methodology), in PLS-SEM path analysis, the square root of AVE should be higher than the correlation coefficient between the variables to satisfy the Fornell-Larcker criterion. The developed construct based on the definition of the first hypothesis has created an acceptable range of discriminant validity.

Table 5-22-Discriminant Validity based on Fornell-Larcker criterion of Hypothesis 1.

	DPP	Supply drivers
DPP	0.87	
Supply drivers	0.825	0.886

In conclusion, the quality criteria, discriminant validity, composite reliability, path coefficient, T-statistic, and R-squared values showed that the first hypothesis's research construct was fitted to the applied data. Overall, SC drivers change the DPP level positively in the leagile SC strategy, and therefore the first hypothesis (H_1) is supported.

5.6.1 Analysis of Sub-Hypothesis 1-1

The first hypothesis consists of five sub-hypotheses based on the assigned SC drivers: production, location, information, transportation, and inventory. After conducting CFA, the transportation driver was removed from the construct, so the transportation sub-hypothesis was eliminated. Hence, four hypotheses based on four SC drivers remained in the construct. The construct of sub-hypothesis 1-1 (H_{1-1}) was defined to assess whether the production driver causes the change in DPP level in leagile SC. Figure 5-12 shows the path coefficient and T-value of the developed construct based on the sub-hypothesis 1-1 (H_{1-1}).

Furthermore, as expected from the CFA analysis, factor loading of all indicators has had a satisfactory level higher than the threshold limit. The bootstrapping test was conducted to check the path coefficient and T-statistics between the two variables (i.e., production driver & DPP) via a 5000-re-sampling procedure. The production driver and DPP have had a path coefficient (0.887) and T-value (38.465) higher than the defined threshold limits of 0.7 and 1.96, respectively. The higher T-statistic value indicates greater evidence against the null hypothesis. A closer T-value to zero (lower than the absolute of ±1.96) represents no significant difference in standard error units.

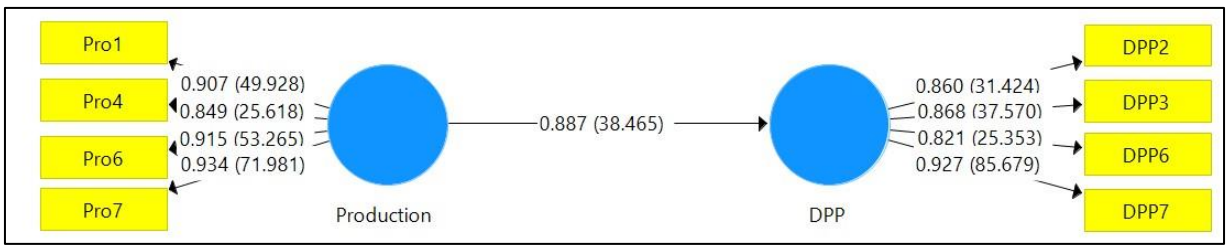


Figure 5-12- Structural model of Sub-hypothesis 1-1– Effect of production driver in the positioning of DPP in leagile supply chain.

Table 5-23 shows the factor loading and T-values of the developed construct related to the definition of the sub-hypothesis 1-1. It is necessary to check the factor loadings and T-values of all approved items by considering the sub- hypothesis 1-1 and its construct to ensure the reliability of the study has not been violated all indicators' T-statistics estimate the construct's stability in the defined confidence interval.

Table 5-23-Hypothesis 1-1-Pls (factor loading) and bootstrapping calculation (T-Values) – Effect of production driver in the positioning of DPP in leagile supply chain.					
	Factor Loading (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
DPP2 <- DPP	0.86	0.859	0.027	31.424	0
DPP3 <- DPP	0.868	0.869	0.023	37.57	0
DPP6 <- DPP	0.821	0.821	0.032	25.353	0
DPP7 <- DPP	0.927	0.927	0.011	85.679	0
Pro1 <- Production	0.907	0.907	0.018	49.928	0
Pro4 <- Production	0.849	0.849	0.033	25.618	0
Pro6 <- Production	0.915	0.915	0.017	53.265	0
Pro7 <- Production	0.934	0.934	0.013	71.981	0

Table 5-24 demonstrates the path coefficient and T-Statistic between two main variables (i.e., production driver & DPP) at a 95% confidence level. Both path coefficient (0.887) and T-statistic (40.536) are higher than threshold limits, and there is no zero between the lower and higher limit of confidence intervals. Hence, it can be concluded that the T-statistic of the main path between the production driver and DPP variable estimates the stability of the construct at the defined confidence interval. Thereby, it can be stated that the first sub-hypothesis (H_{11}) has been approved statistically. However, the quality criteria of the construct have been checked to ensure the reliability and internal consistency of the construct have not been neglected.

Table 5-24-Path analysis of Hypothesis 1-1– Effect of production driver in the positioning of DPP in leagile supply chain.							
	Path Coefficient (O)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	LLCI (2.5%)	ULCI (97.5%)	Support (Yes/No)
Production -> DPP	0.887	0.023	38.465	0	0.839	0.929	Yes

Table 5-25 shows the quality criteria, including Cronbach's Alpha, CR, and AVE for the first sub-hypothesis 1-1. It can be observed that all requirements were higher than defined

threshold limits which approved the reliability and internal consistency of the developed construct for the first sub-hypothesis (H_{1-1}), and this sub-hypothesis has been certified.

To evaluate the sub-hypothesis construct (H_{1-1}), it is required to consider the R-squared value alongside the path coefficient and T-value to ensure the developed construct can produce a reasonable prediction about the sub-hypothesis model. R-squared has been computed and reported for DPP as an endogenous variable to determine how the sub-hypothesis 1-1and its developed construct can estimate the variance. Considering the T-Value (38.465) at 95% of intervals level and the R-squared value (0.788), it can be concluded that the developed construct for the first sub-hypothesis was fitted to the collected data. Also, it can be stated that DPP can be explained 78.8% of the variance of the developed construct of H_{1-1} precisely.

Table 5-25-Quality criteria of Hypothesis 1-1 – Effect of production driver in the positioning of DPP in leagile supply chain.

	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)	R-squared
DPP	0.892	0.925	0.757	0.788
Production	0.923	0.946	0.814	--

Table 5-26 shows the discriminant validity based on the Fornell-Larcker criterion of sub hypothesis 1-1. As explained in PLS-SEM path analysis, the square root of AVE should be higher than the correlation coefficient between the variables to satisfy the Fornell-Larcker criterion. The developed construct based on the definition of the first sub-hypothesis has created an acceptable range of discriminant validity.

Table 5-26-Discriminant validity of Hypothesis 1-1 based on the Fornell-Larcker criterion

	DPP	Production
DPP	0.870	
Production	0.858	0.902

In conclusion, the quality criteria, discriminant validity, composite reliability, path coefficient, T-statistic, and R-squared values were shown that the research construct of the sub-hypothesis

(H_{1-1}) was fitted to the applied data. The production driver causes the DPP level change in the leagile SC strategy; therefore, the first sub-hypothesis (H_{1-1}) is supported.

5.6.2 Analysis of Sub-Hypothesis 1-2

The construct of sub-hypothesis 1-2 (H_{1-2}) was defined to assess whether the location driver causes the change of DPP level in leagile SC. Figure 5-13 shows the path coefficient and T-value of the developed construct based on the sub-hypothesis 1-2 (H_{1-2}). Furthermore, as expected from the CFA analysis, factor loading of all indicators has had a satisfactory level higher than the threshold limit. The bootstrapping test was conducted to check the path coefficient and T-statistics between the two variables (i.e., location driver & DPP) via a 5000re-sampling procedure. The location driver and DPP have had a path coefficient (0.895) and T-value (44.443) higher than the defined threshold limits of 0.7 and 1.96, respectively. The higher T-statistic value indicates more significant evidence against the null hypothesis. A closer T-value to zero (lower than the absolute of ±1.96) represents no significant difference in standard error units.

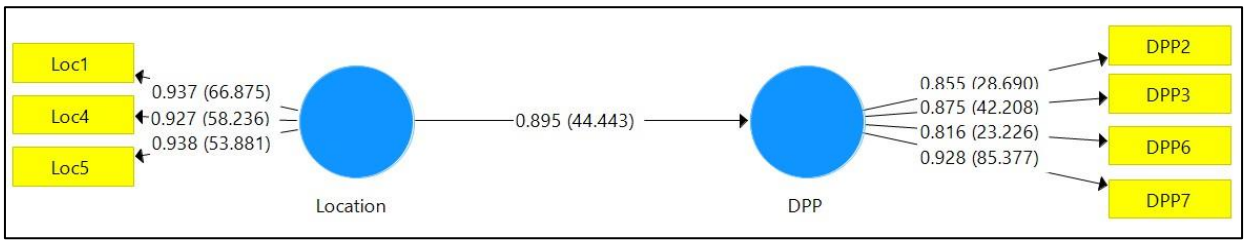


Figure 5-13- Structural model of sub-hypothesis 1-2– Effect of location driver in the positioning of DPP in leagile supply chain.

Table 5-27 demonstrates the path coefficient and T-Statistic between two main variables (i.e., location driver & DPP) at a 95% confidence level. Both path coefficient (0.895) and T-value (44.443) were higher than threshold limits, and there is no zero between the lower and higher limit of confidence intervals. Hence, it can be concluded that the T-statistic of the main path between the location driver and DPP variable estimates the stability of the construct at the defined confidence interval. Thereby, it can be stated that the first sub-hypothesis (H_{1-2}) has been approved statistically. However, the quality criteria of the construct have been checked to ensure the reliability and internal consistency of the construct have not been neglected.

Table 5-27-Path analysis of Hypothesis 1-2– Effect of location driver in the positioning of DPP in Leagile supply chain.							
	Path Coefficient (O)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	LLCI (2.5%)	ULCI (97.5%)	Support (Yes/No)
Location -> DPP	0.895	0.02	44.443	0	0.854	0.933	Yes

Table 5-28 shows the factor loading and T-values of the developed construct related to the definition of sub-hypothesis 1-2. It is necessary to check the factor loadings and T-values of all approved items by considering the sub- hypothesis 1-2 and its construct to ensure the reliability of the study has not been violated. All indicators' T-statistics estimate the construct's stability in the defined confidence interval.

Table 5-28-Hypothesis 1-2-Pls (factor loading) and bootstrapping calculation (T-Values) – Effect of location driver in the positioning of DPP in leagile supply chain.					
	Factor Loading (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
DPP2 <- DPP	0.855	0.854	0.03	28.69	0
DPP3 <- DPP	0.875	0.876	0.021	42.208	0
DPP6 <- DPP	0.816	0.814	0.035	23.226	0
DPP7 <- DPP	0.928	0.929	0.011	85.377	0
Loc1 <- Location	0.937	0.937	0.014	66.875	0
Loc4 <- Location	0.927	0.927	0.016	58.236	0
Loc5 <- Location	0.938	0.937	0.017	53.881	0

Table 5-29 shows the quality criteria, including Cronbach's Alpha, CR, and AVE for the first sub-hypothesis 1-2. It can be observed that all criteria were higher than defined threshold limits which approved the reliability and internal consistency of the developed construct for the first sub-hypothesis (H_{1-2}), and this sub-hypothesis has been certified.

To evaluate the fitness of the sub-hypothesis construct (H_{1-2}), it is required to consider the R-squared value alongside the path coefficient and t-value to ensure the developed construct can produce a reasonable prediction about the sub-hypothesis model. R-squared has been computed and reported for DPP as an endogenous variable to determine how the sub-

hypothesis 1-2 and its developed construct can strongly estimate the variance. Considering the T-Value (44.443) at 95% of intervals level and R-squared value (0.802), it can be concluded that the developed construct for the first sub-hypothesis was fitted to the collected data. Also, it can be stated that DPP can be explained 80.2% of the variance of the developed construct of H_{1-2} precisely.

Table 5-29-Quality criteria of Hypothesis 1-2 – Effect of location driver in the positioning of DPP in leagile supply chain.

	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)	R-squared
DPP	0.892	0.925	0.756	0.802
Location	0.927	0.954	0.873	---

Table 5-30 shows the discriminant validity based on the Fornell-Larcker criterion of sub hypothesis 1-2. As explained in PLS-SEM path analysis, the square root of AVE should be higher than the correlation coefficient between the variables to satisfy the Fornell-Larcker criterion. The developed construct based on the definition of the first sub-hypothesis has created an acceptable range of discriminant validity.

Table 5-30-Discriminant validity of Hypothesis 1-2 based on the Fornell-Larcker criterion

	DPP	Location
DPP	0.869	
Location	0.863	0.934

In conclusion, the quality criteria, discriminant validity, composite reliability, path coefficient, T-statistic, and R-squared values were shown that the research construct of the sub-hypothesis (H_{1-2}) was fitted to the applied data. Location driver causes a change in the DPP level positively in the leagile SC strategy; therefore, the second sub-hypothesis (H_{1-2}) is supported.

5.6.3 Analysis of Sub-Hypothesis 1-3

The construct of sub-hypothesis 1-3 (H_{1-3}) was defined to assess whether the inventory driver changes the DPP level in leagile SC. Figure 5-14 shows the path coefficient and T-value of

the developed construct based on the sub-hypothesis 1-3 (H_{1-3}). Furthermore, as expected from the CFA analysis, factor loading of all indicators has had a satisfactory level higher than the threshold limit. The bootstrapping test was conducted to check the path coefficient and T-statistics between the two variables (i.e., inventory driver & DPP) via a 5000-re-sampling procedure. The inventory driver and DPP have had path coefficients (0.931) and T-value (59.165) higher than defined threshold limits of 0.7 and 1.96, respectively. The higher T-statistic value indicates greater evidence against the null hypothesis. A closer T-value to zero (lower than the absolute of ±1.96) represents no significant difference in standard error units.

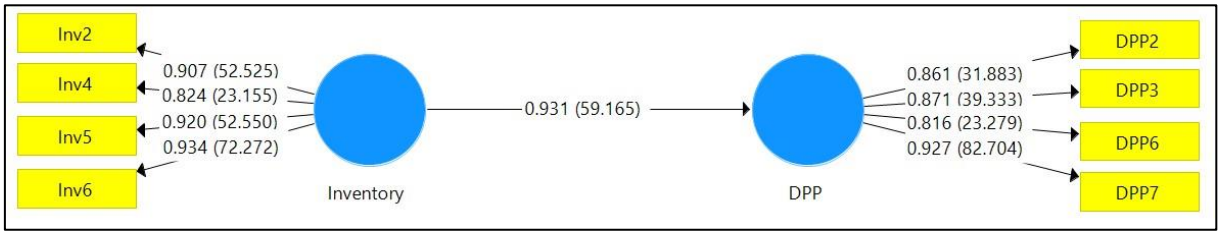


Figure 5-14- Structural model of Hypothesis 1-3– Effect of inventory driver in the positioning of DPP in leagile supply chain.

Table 5-31 shows the path coefficient and T-Statistic between two main variables (i.e., inventory driver & DPP) at a 95% confidence level. Both path coefficient (0.931) and T-value (59.165) were higher than threshold limits, and there is no zero between the lower and higher limit of confidence intervals. Hence, it can be concluded that the T-statistic of the main path between the inventory driver and DPP variable estimates the construct's stability at the defined confidence interval. Thereby, the first sub-hypothesis (H_{1-3}) has been approved statistically. However, the quality criteria of the construct have been checked to ensure the reliability and internal consistency of the construct have not been neglected.

Table 5-31-Path analysis of Hypothesis 1-3– Effect of inventory driver in the positioning of DPP in leagile supply chain.

	Path Coefficient (O)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	LLCI (2.5%)	ULCI (97.5%)	Support (Yes/No)
Inventory -> DPP	0.931	0.016	59.165	0	0.898	0.958	Yes

Table 5-32 shows the factor loading and T-values of indicators belonging to the developed construct based on the definition of sub-hypothesis 1-3. It is necessary to check the factor loadings and T-values of all approved items by considering the sub- hypothesis 1-3 and its construct to ensure the reliability of the study has not been violated. All indicators' T-statistics estimate the construct's stability in the defined confidence interval.

Table 5-32-Hypothesis 1-3-Pls (factor loading) and bootstrapping calculation (T-Values) – Effect of inventory driver in the positioning of DPP in leagile supply chain.

	Factor Loading (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
DPP2 <- DPP	0.861	0.86	0.027	31.883	0
DPP3 <- DPP	0.871	0.872	0.022	39.333	0
DPP6 <- DPP	0.816	0.814	0.035	23.279	0
DPP7 <- DPP	0.927	0.927	0.011	82.704	0
Inv2 <- Inventory	0.907	0.907	0.017	52.525	0
Inv4 <- Inventory	0.824	0.823	0.036	23.155	0
Inv5 <- Inventory	0.92	0.919	0.017	52.55	0
Inv6 <- Inventory	0.934	0.934	0.013	72.272	0

Table 5-33 shows the quality criteria, including Cronbach's Alpha, CR, and AVE for the first sub-hypothesis 1-3. It can be observed that all criteria were higher than defined threshold limits which approved the reliability and internal consistency of the developed construct for the first sub-hypothesis (H_{1-3}), and this sub-hypothesis has been certified. To evaluate the fitness of the sub-hypothesis construct (H_{1-3}) to the collected data, it is required to consider the R-squared value alongside the path coefficient and T-value to ensure the developed construct can produce a reasonable prediction about the sub-hypothesis model.

R-squared has been computed and reported for DPP as an endogenous variable to determine how the sub-hypothesis 1-3 and its developed construct can strongly estimate the variance. Considering the T-Value (59.165) at 95% of intervals level and the R-squared value (0.867), it can be concluded that the developed construct for the first sub-hypothesis was fitted to the collected data. Also, it can be stated that DPP can be explained 86.7% of the variance of the developed construct of H_{1-3} precisely.

Table 5-33-Quality criteria of Hypothesis 1-3 – Effect of inventory driver in the positioning of DPP in leagile supply chain.				
	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)	R-squared
DPP	0.892	0.925	0.756	0.867
Inventory	0.918	0.943	0.805	--

Table 5-34 shows the discriminant validity based on the Fornell-Larcker criterion of sub hypothesis 1-3. As explained in PLS-SEM path analysis, the square root of AVE should be higher than the correlation coefficient between the variables to satisfy the Fornell-Larcker criterion. The developed construct based on the definition of the first sub-hypothesis has created an acceptable range of discriminant validity.

Table 5-34-Discriminant validity of Hypothesis 1-3 based on the Fornell-Larcker criterion		
	DPP	Inventory
DPP	0.870	
Inventory	0.831	0.897

In conclusion, the quality criteria, discriminant validity, composite reliability, path coefficient, T-statistic, and R-squared values showed that sub-hypothesis's research construct (H_{1-3}) was fitted to the applied data. Inventory driver change in the DPP level positively in the leagile SC strategy; therefore, the third sub-hypothesis (H_{1-3}) is supported.

5.6.4 Analysis of Sub-Hypothesis 1-5

The construct of sub-hypothesis 1-5 (H_{1-5}) was defined to assess whether the information driver causes the change of DPP level in leagile SC. Figure 5-15 shows the path coefficient and T-value of the developed construct based on the sub-hypothesis 1-5 (H_{1-5}). Furthermore, as expected from the CFA analysis, factor loading of all indicators has had a satisfactory level higher than the threshold limit. The bootstrapping test was conducted to check the path coefficient and T-statistics between the two variables (i.e., information driver & DPP) via a 5000-re-sampling procedure. The information driver and DPP have had path coefficients (0.902) and T-value (47.206) higher than defined threshold limits of 0.7 and 1.96,

respectively. The higher T-statistic value indicates greater evidence against the null hypothesis. A closer T-value to zero (lower than the absolute of ±1.96) represents no significant difference in standard error units.

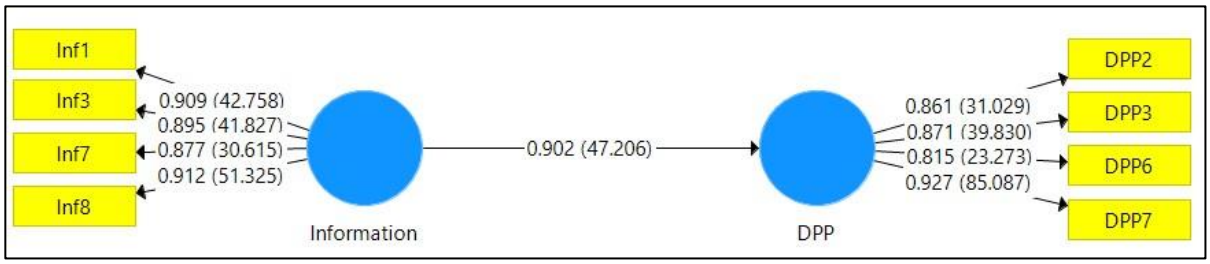


Figure 5-15- Structural model of sub-hypothesis 1-5 – Effect of information driver in the positioning of DPP in leagile supply chain.

Table 5-35 shows the path coefficient and T-Statistic between two main variables (i.e., information driver & DPP) at a 95% confidence level. Both path coefficient (0.902) and T-value (47.206) were higher than threshold limits, and there is no zero between the lower and higher limit of confidence intervals. Hence, it can be concluded that the T-statistic of the main path between the information driver and DPP variable estimates the stability of the construct at the defined confidence interval. Thereby, it can be stated that the first sub-hypothesis (H_{15}) has been approved statistically. However, the quality criteria of the construct have been checked to ensure the reliability and internal consistency of the construct have not been neglected.

Table 5-35-Path analysis of Hypothesis 1-5– Effect of information driver in the positioning of DPP in leagile supply chain.

	Path Coefficient (O)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	LLCI (2.5%)	ULCI (97.5%)	Support (Yes/No)
Information -> DPP	0.902	0.019	47.206	0	0.862	0.938	Yes

Table 5-36 shows the factor loading and T-values of indicators belonging to the developed construct based on the definition of sub-hypothesis 1-5. It is necessary to check the factor loadings and T-values of all approved items by considering the sub-hypothesis 1-5 and its construct to ensure the reliability of the study has not been violated. It can be observed that all indicators' T-statistics estimate the construct's stability in the defined confidence interval.

Table 5-36-Hypothesis 1-5- Pls (factor loading) and bootstrapping calculation (T-Values) – Effect of information driver in the positioning of DPP in leagile supply chain.					
	Factor Loading (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
DPP2 <- DPP	0.861	0.86	0.028	31.029	0
DPP3 <- DPP	0.871	0.872	0.022	39.83	0
DPP6 <- DPP	0.815	0.814	0.035	23.273	0
DPP7 <- DPP	0.927	0.927	0.011	85.087	0
Inf1 <- Information	0.909	0.908	0.021	42.758	0
Inf3 <- Information	0.895	0.895	0.021	41.827	0
Inf7 <- Information	0.877	0.876	0.029	30.615	0
Inf8 <- Information	0.912	0.912	0.018	51.325	0

Table 5-37 shows the quality criteria, including Cronbach's Alpha, CR, and AVE for the first sub-hypothesis 1-5. It can be observed that all criteria were higher than defined threshold limits which approved the reliability and internal consistency of the developed construct for the first sub-hypothesis (H_{1-5}), and this sub-hypothesis has been certified.

To evaluate the fitness of the sub-hypothesis construct (H_{1-5}) to the collected data, it is required to consider the R-squared value alongside the path coefficient and T-value to ensure the developed construct can produce a reasonable prediction about the sub-hypothesis model. R-squared has been computed and reported for DPP as an endogenous variable to determine how the sub hypothesis 1-5 and its developed construct can strongly estimate the variance.

Considering the T-Value (54.902) at 95% of intervals level and R-squared value (0.841), it can be concluded that the developed construct for the first sub-hypothesis was fitted to the collected data. Also, it can be stated that DPP can be explained 84.1% of the variance of the developed construct of H_{1-5} precisely.

Table 5-37-Quality criteria of Hypothesis 1-5 – Effect of information driver in the positioning of DPP in leagile supply chain.				
	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)	R-squared
DPP	0.892	0.925	0.756	0.814
Information	0.92	0.944	0.807	--

Table 5-38 shows the discriminant validity based on the Fornell-Larcker criterion of sub hypothesis 1-5. As explained in PLS-SEM path analysis, the square root of AVE should be higher than the correlation coefficient between the variables to satisfy the Fornell-Larcker criterion. The developed construct based on the definition of the first sub-hypothesis has created an acceptable range of discriminant validity.

Table 5-38-Discriminant validity of Hypothesis 1-5 based on the Fornell-Larcker criterion		
	DPP	Information
DPP	0.87	
Information	0.801	0.898

In conclusion, the quality criteria, discriminant validity, composite reliability, path coefficient, T-statistic, and R-squared values showed that sub-hypothesis's research construct (H_{1-5}) was fitted to the applied data. Information driver causes the change of the DPP level positively in the leagile SC strategy; therefore, the fifth sub-hypothesis (H_{1-5}) is supported.

5.7 Analysis of Hypothesis 2

The second hypothesis is whether DPP adoption leads to better supply chain performance for companies within industrial clusters. To test the second hypothesis, all approved indicators of DPP and approved indicators of TSCV acquired from CFA analysis were inserted into this stage. Total supply chain value (TSCV) has been defined to show the performance of industrial companies. The developed construct of the second hypothesis (H_2) has been shown in figure 5-16. The bootstrapping test was conducted to check the path coefficient and T-statistics between the two variables (i.e., DPP & TSCV variables) via a 5000-re-sampling

procedure. DPP and TSCV driver indicators have path coefficients and T-values higher than defined threshold limits of 0.7 and 1.96, respectively. However, the focus of this study was to determine the path coefficient between two main factors, which proved that there is a direct effect between DPP and TSCV due to obtaining a positive correlation.

Figure 5-16 shows that the DPP-TSCV has had a path coefficient of 0.910 @ 95% of interval level, demonstrating higher reliability of the predictive power of the path coefficient. The bootstrap procedure has been used as a hypothesis testing method to calculate the T-value of 5000 re-samplings, allowing testing of the assigned assumption for the construct. The higher T-statistic value shows greater evidence against the null hypothesis. A closer T-value to zero (lower than the absolute of ±1.96) represents no significant difference in standard error units. A closer T-value to zero shows no adequate evidence to demonstrate an effect between two variables at the predefined confident interval. Performed analysis shows that the stability of estimates via bootstrapping method was significant, and the second hypothesis was supported. It means DPP adoption leads to better supply chain performance for companies within industrial clusters.

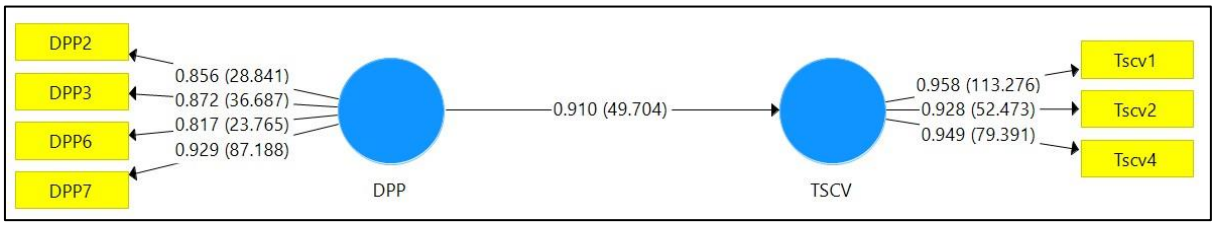


Figure 5-16- Structural model of Hypothesis 2– Effect of decoupling point position in performance of industrial clusters.

Table 5-39 shows the path coefficient and T-Statistics between two main variables (i.e., DPP & TSCV) at a 95% confidence level. It can be seen both values are higher than threshold limits, and there is no zero included between the lower and higher limit of confidence intervals. Hence, it can be concluded that the second hypothesis has been approved statistically; however, the quality criteria of the construct have been checked to ensure the reliability and internal consistency of the construct have not been neglected.

Table 5-39-Path analysis of Hypothesis 2– Effect of decoupling point position in performance of industrial clusters.							
	Path Coefficient (O)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	LLCI (2.5%)	ULCI (97.5%)	Support (Yes/No)
DPP -> TSCV	0.910	0.018	49.704	0	0.873	0.944	Yes

Table 5-40 shows the factor loading and T-values of developed construct indicators based on the second hypothesis's definition. Although it seems this step has been conducted in the CFA section, it is necessary to check the factor loadings and T-values of all approved items by considering the second hypothesis and its construct to ensure the reliability of the study has not been violated. It can be observed that all samples' T-statistics estimate the construct's stability. Furthermore, as expected from the CFA analysis, factor loading of all indicators has had a satisfactory level higher than the threshold limit.

Table 5-40-Hypothesis 2-Pls (factor loading) and bootstrapping calculation (T-Values) – Effect of decoupling point position in performance of industrial clusters.					
	Factor Loading (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
DPP2 <- DPP	0.856	0.854	0.03	28.841	0
DPP3 <- DPP	0.872	0.873	0.024	36.687	0
DPP6 <- DPP	0.817	0.816	0.034	23.765	0
DPP7 <- DPP	0.929	0.929	0.011	87.188	0
Tscv1 <- TSCV	0.958	0.958	0.008	113.276	0
Tscv2 <- TSCV	0.928	0.927	0.018	52.473	0
Tscv4 <- TSCV	0.949	0.949	0.012	79.391	0

Table 5-41 demonstrates the quality criteria for the second hypothesis, including Cronbach's Alpha, CR, and AVE. It can be observed that all requirements were higher than defined threshold limits which approved that the reliability and internal consistency of the developed construct for the second hypothesis have been certified.

Although the R-squared value must not be considered merely to evaluate the model's fitness for the collected data, considering the R-squared value alongside the path coefficient and T-

value can produce a reasonable prediction about the hypothesis model. R-squared has been computed and reported for the DPP variable to determine how the second hypothesis and its developed construct can strongly estimate the variance. By considering the T-Value (49.704) at 95% of intervals level and R-squared value (0.828), it can be concluded that the developed construct for the second hypothesis was fitted to the collected data, and DPP can be explained 82.8% of the variance.

Table 5-41-Quality criteria of Hypothesis 2– Effect of decoupling point position in performance of industrial clusters.

	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)	R-squared
DPP	0.892	0.925	0.756	0.828
TSCV	0.94	0.961	0.893	--

Table 5-42 shows the discriminant validity based on the Fornell-Larcker criterion of Hypothesis 2. As explained in chapter 3 (i.e., research methodology), in PLS-SEM path analysis, the square root of AVE would be higher than the correlation coefficient between the variables to satisfy the Fornell-Larcker criterion. The developed construct based on the definition of the second hypothesis has created an acceptable range of discriminant validity.

Table 5-42-Discriminant validity Hypothesis 2– based on the Fornell-Larcker criterion.

	DPP	TSCV
DPP	0.870	
TSCV	0.810	0.945

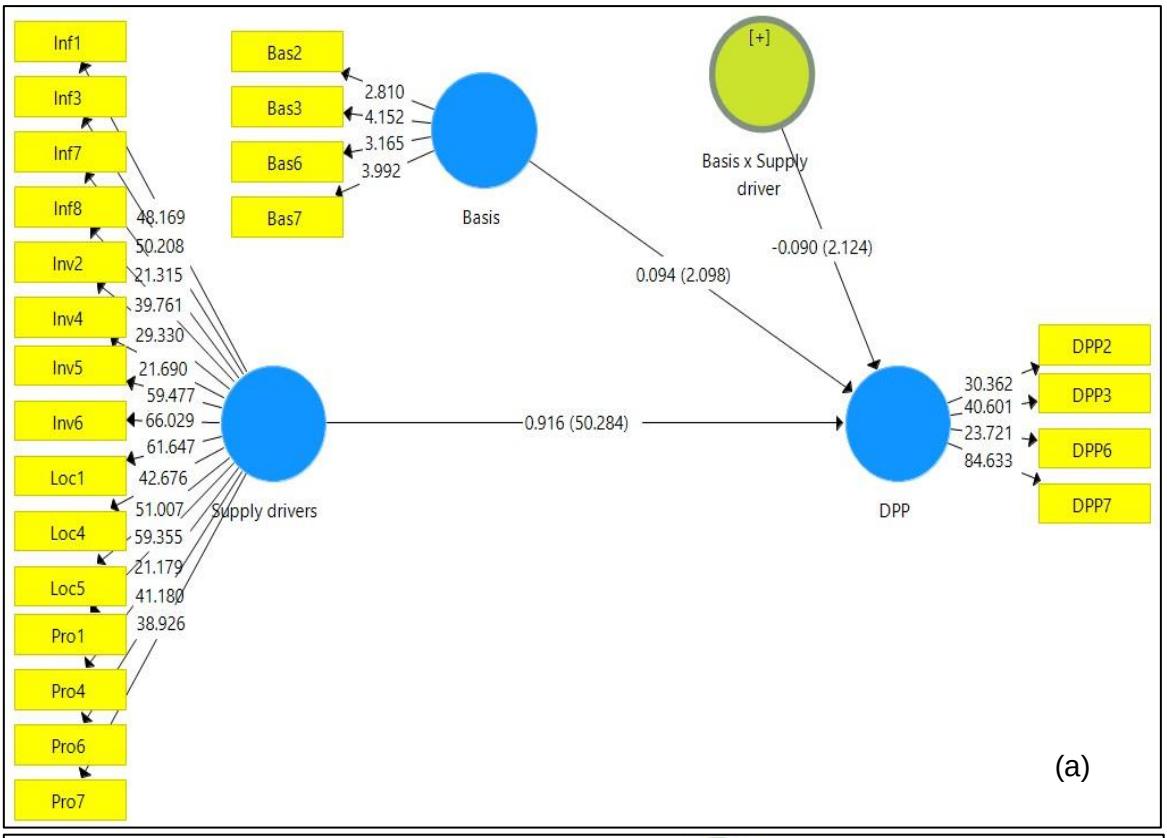
In conclusion, the quality criteria, discriminant validity, composite reliability, path coefficient, T-statistic, and R-squared values were shown that the research construct of the second hypothesis (H_2) was fitted to the applied data. DPP adoption leads to better supply chain performance for companies within industrial clusters, and therefore the second hypothesis (H_2) is supported.

5.8 Hypothesis 3: Basis & Foundation Moderator

This section must analyse the relationship between supply chain drivers and DPP with the existence of the Basis & Foundation factor as a moderator. The indicators of the Basis & Foundation (as a moderator variable) were determined in the CFA section, including Bas 2, Bas 3, Bas 6, and Bas 7.

Figure 5-17 (a) and (b) show the path coefficients (O) and T-values of the third hypothesis model using two-stage and productivity approaches, respectively, by considering the moderation effect between two variables. Although the productivity approach has given a lower value of path coefficient (O) ($\beta = -0.114$ @ $\alpha < 0.05$) and a significant T-value (2.778) in comparison with the two-stage technique ($\beta = -0.090$ @ $\alpha < 0.05$, t-value = 2.124). Nevertheless, there is no difference between the direction of the path analysis (both moderators were shown negative effect) and their obtained significant T-values (higher than 1.96).

As discussed previously, the two-stage and productivity approaches selected the two-stage method to show the indicators' T-values. The two-stage approach was applied to report the outcome of the indicators' bootstrapping test (t-statistics). While the path analysis table is included the outcomes of two-stage and productivity approaches using the bootstrapping test to ensure the third hypothesis has been analysed properly.



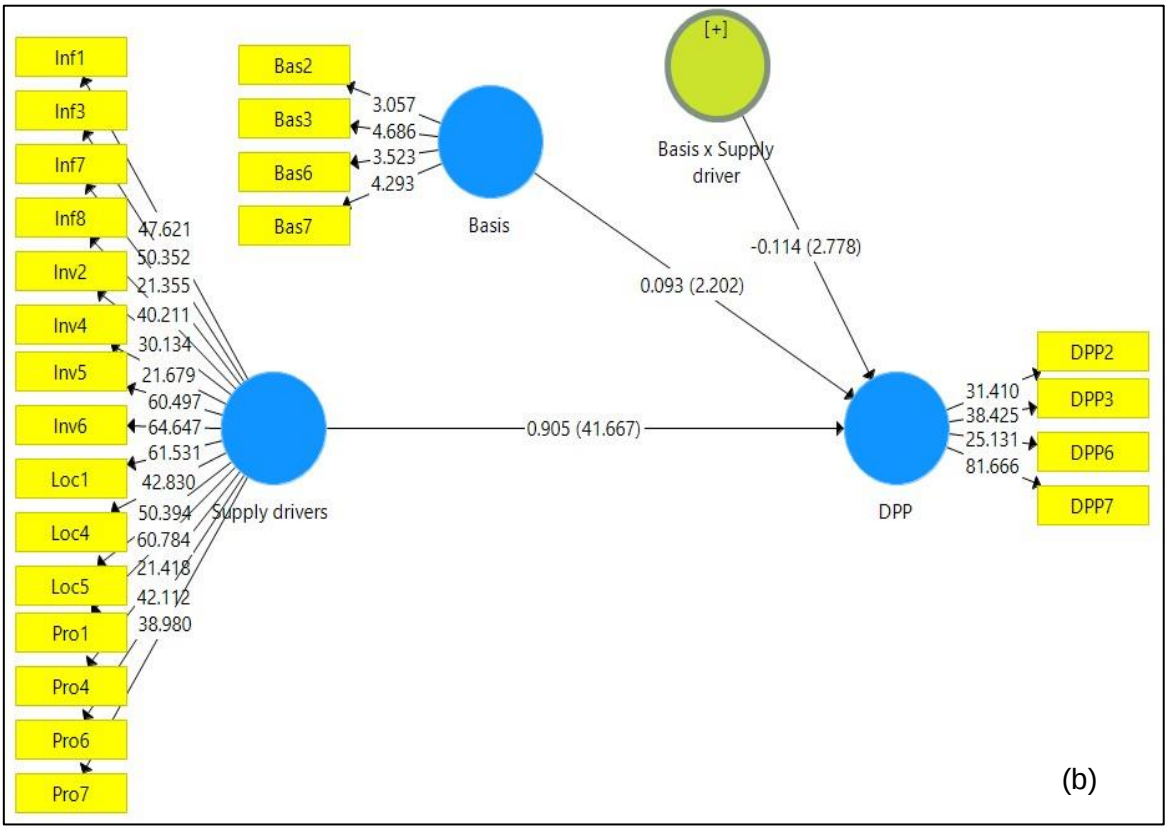


Figure 5-17- (a) shows the structural model of hypothesis 3 using two-stage technique and (b) using productivity approach for the moderation effect. Bootstrapping analysis has been used to determine the path coefficient (t-statistics).

Table 5-43 and Table 5-44 demonstrate the outcomes of the path analysis using the bootstrapping test of the third hypothesis through two-stage and productivity approaches, respectively. The path coefficients (-0.090) between SC driver and DPP are negatively moderated using a two-stage method by the basis & foundation variable. Also, the path coefficients (-0.114) between SC driver and DPP is negatively moderated by the basis & foundation variable using the productivity approach. Furthermore, the productivity approach computed a higher T-Statistic value (2.778) than the two-stage method (2.124). Still, the T-statistics of both directions in the presence of basis & foundation moderator were higher than the defined threshold limit. The higher T-Statistic value showed more robust evidence against the null hypothesis and a significant difference in standard error units.

Table 5-43-Path analysis of hypothesis 3 **using the two-stage approach**. The moderation effect of Basis & Foundation between supply chain drivers and DPP.					
	Path Coefficient (O)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Support (Yes/No)
Basis -> DPP	0.094	0.045	2.098	0.036	
Basis*Supply driver -> DPP	-0.090	0.042	2.124	0.034	Yes
Supply drivers -> DPP	0.916	0.018	50.284	0	
Table 5-44-Path analysis of hypothesis 3 **using the productivity approach**. The moderation effect of Basis & Foundation between supply chain drivers and DPP					
Basis -> DPP	0.093	0.042	2.202	0.028	
Basis*Supply driver -> DPP	-0.114	0.041	2.778	0.005	Yes
Supply drivers -> DPP	0.905	0.022	41.667	0	

Table 5-45 shows the factor loading and T-values of developed construct indicators based on the third hypothesis's definition. The acquired results were computed based on the bootstrapping test when the two-stage approach was applied for the moderator (Basis*Supply driver) variable. Although it seems this step has been conducted in the CFA section, it is necessary to check the factor loadings and T-values of all approved items by considering the third hypothesis and its construct to ensure the reliability of the study has not been violated. It can be observed that all samples' T-statistics estimate the construct's stability. Furthermore,

as expected from the CFA analysis, factor loading of all indicators has had a satisfactory level higher than the threshold limit.

Table 5-45-Using a two-stage approach, the bootstrapping calculation (T-statistics) of hypothesis 3. The moderation effect of Basis & Foundation between supply chain drivers and DPP.

	Factor Loading (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Bas2 <- Basis	0.794	0.732	0.283	2.810	0.005
Bas3 <- Basis	0.948	0.885	0.228	4.152	0
Bas6 <- Basis	0.862	0.790	0.272	3.165	0.002
Bas7 <- Basis	0.911	0.841	0.228	3.992	0
DPP2 <- DPP	0.859	0.858	0.028	30.362	0
DPP3 <- DPP	0.870	0.871	0.021	40.601	0
DPP6 <- DPP	0.820	0.818	0.035	23.721	0
DPP7 <- DPP	0.927	0.927	0.011	84.633	0
Inf1 <- Supply drivers	0.903	0.903	0.019	48.169	0
Inf3 <- Supply drivers	0.901	0.901	0.018	50.208	0
Inf7 <- Supply drivers	0.809	0.809	0.038	21.315	0
Inf8 <- Supply drivers	0.884	0.884	0.022	39.761	0
Inv2 <- Supply drivers	0.850	0.850	0.029	29.330	0
Inv4 <- Supply drivers	0.807	0.806	0.037	21.690	0
Inv5 <- Supply drivers	0.927	0.927	0.016	59.477	0
Inv6 <- Supply drivers	0.931	0.931	0.014	66.029	0
Loc1 <- Supply drivers	0.930	0.930	0.015	61.647	0
Loc4 <- Supply drivers	0.896	0.896	0.021	42.676	0
Loc5 <- Supply drivers	0.909	0.909	0.018	51.007	0
Pro1 <- Supply drivers	0.923	0.923	0.016	59.355	0
Pro4 <- Supply drivers	0.816	0.816	0.039	21.179	0
Pro6 <- Supply drivers	0.891	0.891	0.022	41.180	0
Pro7 <- Supply drivers	0.897	0.897	0.023	38.926	0

Supply drivers*Basis <- Basis*Supply driver	1.012	1.017	0.134	7.567	0

Table 5-46 demonstrates the quality criteria for the third hypothesis, including Cronbach's Alpha, CR, and AVE. It can be observed that all criteria were higher than defined threshold limits which approved that the reliability and internal consistency of the developed construct for the third hypothesis have been certified.

Although the R-squared value would not be considered merely to evaluate the model's fitness for the collected data, considering the R-squared value alongside the path coefficient and T-value can produce a reasonable prediction about the hypothesis model. R-squared has been computed and reported for the DPP variable to determine how the third hypothesis and developed construct can strongly estimate the variance. By considering the T-Value (2.778) of the moderator path (Basis*Supply driver → DPP) at a 95% confidence interval and R-squared value (0.868), it can be concluded that the developed construct for the third hypothesis was fitted to the collected data and DPP can be explained 86.8% of the variance.

Table 5-46-Quality criteria of hypothesis 3 construct using productivity approach. The moderation effect of Basis & Foundation between supply chain drivers and DPP.

	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)	R-squared
Basis	0.911	0.932	0.776	----
Basis*Supply driver	0.99	0.989	0.608	---
DPP	0.892	0.925	0.757	0.868
Supply drivers	0.98	0.982	0.785	----

Table 5-47 shows the discriminant validity based on the Fornell-Larcker criterion of hypothesis 3. As explained in chapter 3 for PLS-SEM path analysis, the square root of AVE would be higher than the correlation coefficient between the variables to satisfy the Fornell-Larcker criterion. The developed construct based on the definition of the third hypothesis has created an acceptable range of discriminant validity.

Table 5-47-Discriminant validity of hypothesis 3 model using productivity approach based on the Fornell -Larker criterion.				
	Basis	Basis*supply driver	DPP	Supply drivers
Basis	0.881			
Basis*Supply driver	0.253	0.78		
DPP	0.094	0.218	0.87	
Supply drivers	0.031	0.15	0.824	0.886

In conclusion, the quality criteria, discriminant validity, composite reliability, path coefficient, T-statistic, and R-squared values were shown that the research construct of the third hypothesis (H_3) was fitted to the applied data. The relationship between supply chain drivers and DPP is moderated by the industrial clusters' Basis & Foundation factor; therefore, the third hypothesis (H_3) is supported. However, suppose the interaction effect is significant between two variables in the presence of the moderator. In that case, it is required to complete the conducted analysis by drawing the interaction plots and applying SSA between variables to realise the direction of the moderation effect.

5.9 Simple slop analysis of H3

As discussed in chapter 3, section 3.10, it is necessary to complete the analysis of the moderation effect by considering the simple slop test (Dawson 2014).

Table 5-48 shows the steps of two-way linear interaction effects to plot the moderation effect via regression analysis. The values have been collected from the outcome of bootstrapping test using SmartPLS software (V 3).

Figure 5-18 shows the disordinal interaction effect of a moderator (i.e., Basis & foundation * supply chain drivers) on the position of DPP. The X-axis represents the independent variable (SC drivers), and Y-axis represents a dependent variable (DPP). The green line shows the effect of basis & foundation moderation with a higher standard deviation (adding one SD unit to the mean value of the moderator), and the red line shows the effect of basis & foundation moderation with a lower standard deviation (subtracting one SD unit from the mean value of moderator). Also, the blue line shows the avenge effect of basis & foundation between supply chain drivers and DPP.

In this study, the moderator's higher effect (level) can be represented as the strong effect of basis & foundation based on the validated measures in the CFA section. The lower moderation effect can be labelled as the weak effect of basis & foundation as a moderator. The strong and weak influence of the moderation effect indicates how the basis & foundation could interact between the IV and DV in the industrial clusters. Within the interaction effect phenomenon, the difference between the higher and lower effects of basis & foundation depends on the value of SC drivers.

The slope of the green line indicated that the higher effect of the moderator increased the DPP value from -0.70 to 0.87 with the gradient of 0.735, while the slope of the lower effect of basis & foundation increased the value of DPP from -1.12 to 0.91 with the slope of 0.98. Hence, by considering the gradients between two lines, the lower effect of the moderator (red line) has a more significant influence on the negative values of the DPP compared to the higher effect of the moderator. Moreover, a cross-over point (0.85, 0.75) occurred at the top-right corner of the graph, which shows the moderator (i.e., basis & foundation) has interacted between IV and DV at higher positive values rather than negative values of the DPP.

Furthermore, before the interaction effect (cross-over point), the position of the higher effect of basis & foundation (i.e., green line) was more significant than the lower effect of the moderator. While after the interaction point, the lower impact of the moderator (i.e., red line) was higher than the higher effect. Indeed, the interaction effect converted from a higher (green line) to a lower (red line) effect after the interaction point. Hence, this phenomenon shows that the lower effect of the moderator (red line) has a greater impact on the SC driver values than the higher effect of basis & foundation (green line) after the cross-over point. In other words, the moderator has a minor negative impact on the SC driver after the interaction point where the SC driver has had higher values. This fact was matched with the obtained results of the negative path coefficient of the moderation effect (i.e., factor loading of Basis & foundation * Supply drivers is -0.114).

Moreover, on the down-left corner of the graph (where the SC drivers and DPP have a negative value), there is a more significant variance between the higher and lower effect of the moderators' lines (i.e., a vertical gap between red and green lines). There is a small vertical gap between the red and green lines after the cross-over point (orange point in the graph), where the SC driver has a maximum positive value. It shows the variance between the higher and lower moderation effects was insignificant.

Table 5-48-The worksheet plots of two-way linear interaction effects via regression analysis (PLS and bootstrapping tests) to conduct simple slope analysis (adapted from (Dawson 2014)).	
Path Coefficients	**Values**
Independent variable (IV= Supply Chain Drivers)	0.905
Moderator (Basis)	0.093
Interaction (Supply chain Drivers* Basis & Foundation)	-0.114
Dependent variable	DPP
Intercept / Constant	0
Means / SDs of variables:	**Values**
Mean of the independent variable	0.899
SD of the independent variable	0.022
Mean of moderator	0.087
SD of moderator	0.042

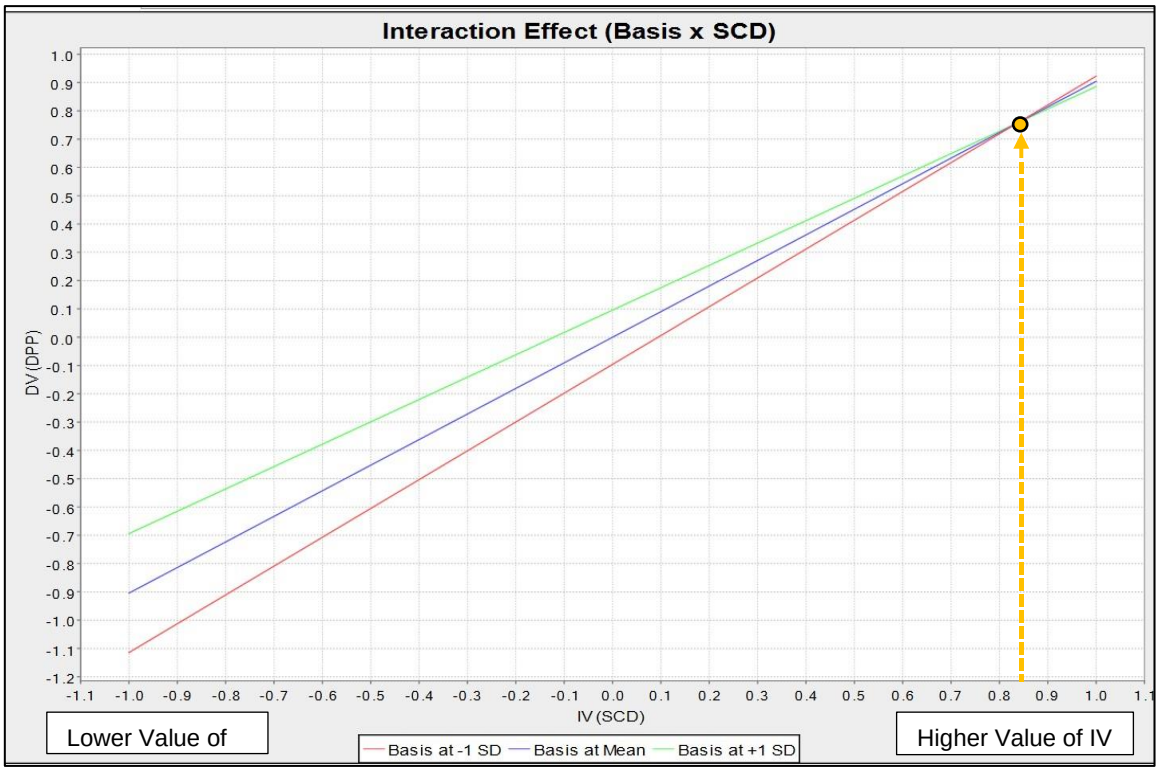


Figure 5-18- The simple slope analysis of the interaction effect (basis & foundation *supply chain drivers) on the position of DPP related to the third hypothesis.

5.9.1 Hypothesis 3-1: The relation between the production driver and DPP is moderated by the Basis & Foundation

In this section, it is required to analyse the relationship between production and DPP with the existence of the basis & foundation factor as a moderator. The indicators of the Basis & Foundation (as a moderator variable) were determined in the CFA, including Bas 2, Bas 3, Bas 6, and Bas 7. Also, within the CFA, the production indicators were listed as Pro 1, Pro 4, Pro 6, and Pro 7. Figure 5-19 shows the path coefficients (O) and T-values of the sub hypothesis model 3-1 using the productivity approach by considering the moderation effect between two variables (i.e., Production → DPP).

The path coefficient (O) of the moderation effect (i.e., Basis & Foundation * Production) was computed ($\beta = -0.128$ @ $\alpha < 0.05$) and the T-value was (1.396). The obtained T-value was insignificant (lower than 1.96) using the bootstrapping test. The obtained path coefficient of the moderation effect is negative, which shows a reverse correlation between the moderation effect and DPP. Furthermore, the bootstrapping analysis also showed that the path analysis based on the definition of sub hypothesis (3-1) was rejected between basis & foundation and DPP (basis & foundation →DPP), where the path coefficient was ($\beta = 0.090$ @ $\alpha < 0.05$) and the T-value (1.221). Although the bootstrapping analysis also showed that the developed structural model based on the definition of sub-hypothesis (3-1) was rejected, further investigations, including the analysis of factor loadings for the indicators, have been conducted to ensure the remarked concluded was reliable.

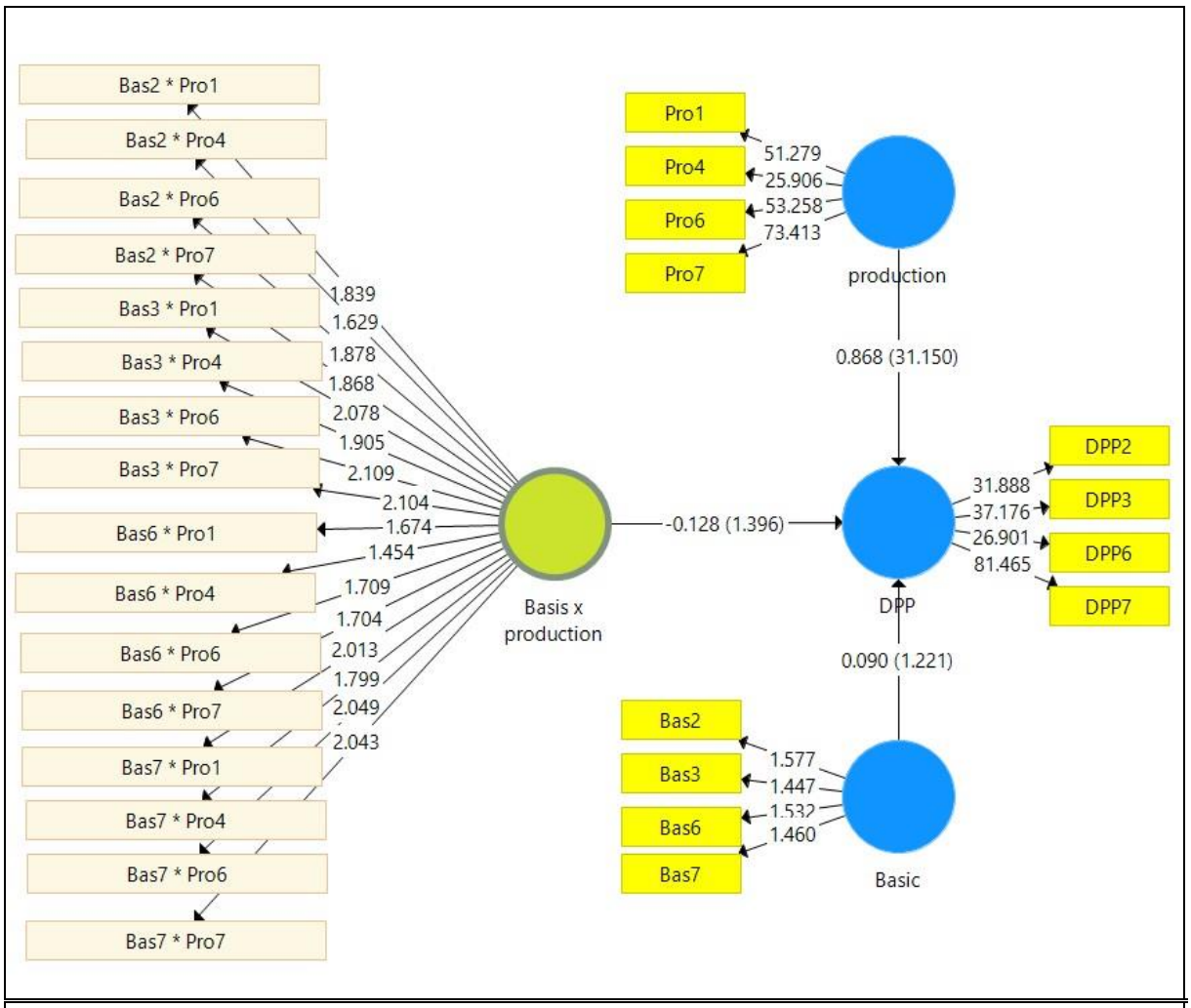


Figure 5-19- The structural model of hypothesis 3-1. Bootstrapping calculation shows the path coefficient (T-statistics) of the moderation effect (i.e., Basis & Foundation) between production driver and DPP.

Table 5-49 shows the T-values and factor loadings of the indicators associated with the structural model of $H_{3\text{-}1}$. It can be observed that the obtained T-Statistics of the indicators belonging to the moderation effect (i.e., Basis & Foundation * production) were lower than the satisfactory limit (|±1.96|), as well as the P-value of most of the items, was higher than 0.5. Hence, it can be concluded that the indicators of the moderation effect (Basis & Foundation * production) did not interact significantly between the production driver and DPP.

Table 5-49-Bootstrapping calculation (T-statistics) of the sub-hypothesis 3-1. The production driver and DPP are moderated by the Basis & Foundation.

	Factor Loadings (O)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values

Bas2 <- Basis	0.797	0.506	1.577	0.115
Bas2 * Pro1 <- Basis * production	0.768	0.417	1.839	0.066
Bas2 * Pro4 <- Basis * production	0.751	0.461	1.629	0.103
Bas2 * Pro6 <- Basis * production	0.757	0.403	1.878	0.061
Bas2 * Pro7 <- Basis * production	0.765	0.41	1.868	0.062
Bas3 <- Basis	0.947	0.655	1.447	0.148
Bas3 * Pro1 <- Basis * production	0.723	0.348	2.078	0.038
Bas3 * Pro4 <- Basis * production	0.719	0.377	1.905	0.057
Bas3 * Pro6 <- Basis * production	0.712	0.338	2.109	0.035
Bas3 * Pro7 <- Basis * production	0.725	0.345	2.104	0.035
Bas6 <- Basis	0.864	0.564	1.532	0.126
Bas6 * Pro1 <- Basis * production	0.741	0.442	1.674	0.094
Bas6 * Pro4 <- Basis * production	0.714	0.491	1.454	0.146
Bas6 * Pro6 <- Basis * production	0.724	0.424	1.709	0.088
Bas6 * Pro7 <- Basis * production	0.731	0.429	1.704	0.088
Bas7 <- Basis	0.909	0.623	1.46	0.144
Bas7 * Pro1 <- Basis * production	0.69	0.343	2.013	0.044
Bas7 * Pro4 <- Basis * production	0.684	0.38	1.799	0.072
Bas7 * Pro6 <- Basis * production	0.677	0.33	2.049	0.041
Bas7 * Pro7 <- Basis * production	0.691	0.338	2.043	0.041
DPP2 <- DPP	0.86	0.027	31.888	0
DPP3 <- DPP	0.865	0.023	37.176	0
DPP6 <- DPP	0.826	0.031	26.901	0
DPP7 <- DPP	0.925	0.011	81.465	0
Pro1 <- production	0.907	0.018	51.279	0
Pro4 <- production	0.849	0.033	25.906	0
Pro6 <- production	0.915	0.017	53.258	0
Pro7 <- production	0.934	0.013	73.413	0

Table 5-50 demonstrates the path coefficient and T-Statistic of the pathway between three variables: production, DPP, and basis & foundation. The moderation effect has been defined as a production * basis & foundation, which is the main part of the structural model based on the definition of sub-hypothesis (3-1). The T-Statistic value between moderator and DPP

(1.396 @ P-value > 0.05), as well as the T-value of the moderator variable (1.221 @ P-value > 0.05), were lower than |±1.96| and therefore, the path analysis of the moderation effect was not supported the sub-hypothesis 3-1.

Table 5-50-Path analysis of hypothesis 3-1. The production driver and DPP are moderated by the Basis & Foundation.

	Path Coefficient (O)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	LLCI (2.5%)	ULCI (97.5%)	Support (Yes/No)
Basis -> DPP	0.09	0.074	1.221	0.222	-0.085	0.19	
Basis*production -> DPP (H_{3-1})	-0.128	0.092	1.396	0.163	-0.224	0.148	No
Production -> DPP	0.868	0.028	31.15	0	0.81	0.916	

Table 5-51 demonstrates the quality criteria, including Cronbach's Alpha, CR, and AVE for the sub-hypothesis 3-1. It can be observed that all quality criteria were accepted. However, due to the unsatisfactory values of T-Statistics, P-Values, and construct intervals, the sub hypothesis 3-1 was not proved. Hence, it is unnecessary to investigate the discriminant validity of hypothesis 3-1 based on the Fornell-Larcker criterion.

Table 5-51-Quality criteria of hypothesis 3-1 construct. The production driver and DPP is moderated by the Basis & Foundation.

	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)	R-squared
Basis	0.911	0.933	0.776	----
Basis*production	0.962	0.961	0.610	---
DPP	0.892	0.925	0.757	0.802
production	0.923	0.946	0.814	----

In conclusion, the T-values of the indicators, T-Statistics of the paths, and P-values were shown that the research construct of the sub-hypothesis (H_{3-1}) was not fitted to the applied data. In fact, the relation between production driver and DPP has not been moderated by the Basis & Foundation, and therefore the sub-hypothesis (H_{3-1}) is not supported.

5.9.2 Hypothesis 3-2: The relation between location driver and DPP is moderated by the Basis & Foundation

In this section, the relationship between location and DPP with the existence of the Basis & Foundation as a moderator was analysed. The indicators of the Basis & Foundation (as a moderator variable) were reported in the previous section after conducting CFA, including Bas 2, Bas 3, Bas 6, and Bas 7. Also, within the CFA, the location indicators were listed as Loc1, Loc4, and Loc 5. Figure 5-20 shows the path coefficients (O) and t-values of the developed construct based on the definition of the sub-hypothesis 3-2 using the productivity approach by considering the moderation effect between two variables (Location→DPP). The path coefficient (O) of moderation effect (i.e., Basis & Foundation * Location→DPP) was computed ($\beta = -0.135$ @ $\alpha < 0.05$) and the T-value was (3.435). The obtained path coefficient of the moderation effect is negative, which shows that there was a reverse correlation between the moderation effect and DPP. Although the path analysis's obtained tvalue (3.435) was significant (higher than 1.96) using the bootstrapping test, it is necessary to conduct further analysis to investigate whether the indicators of moderation effect were accepted.

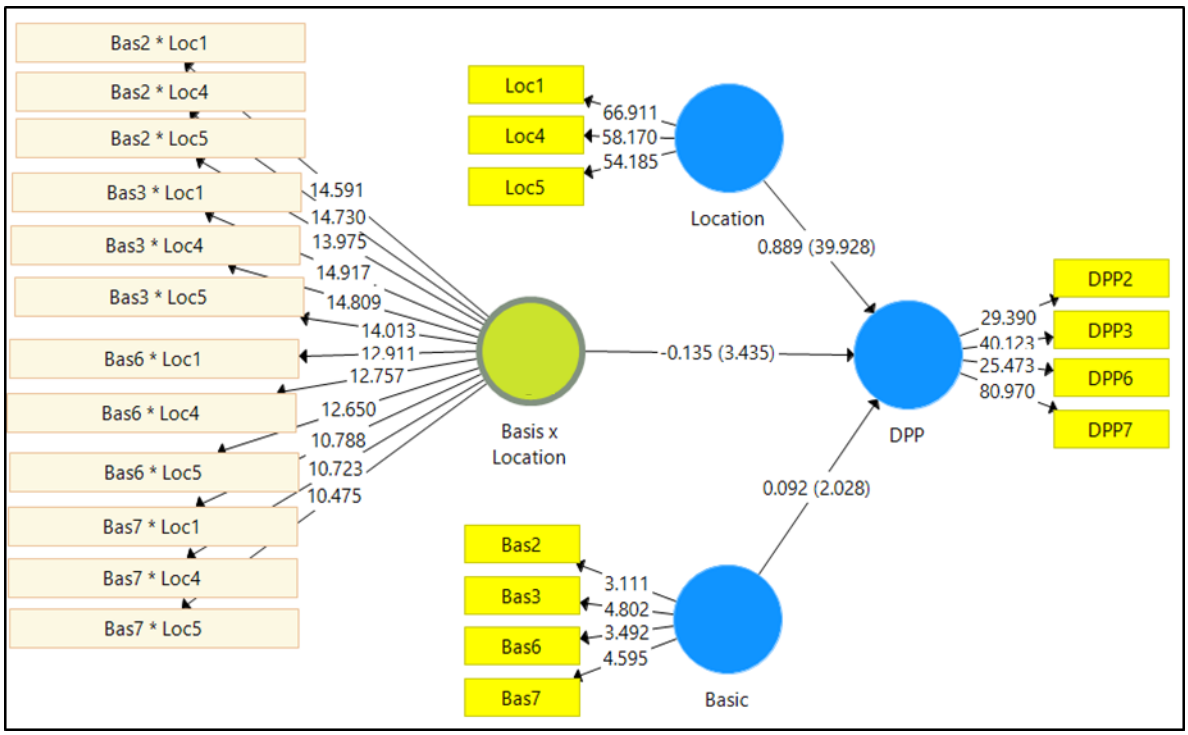


Figure 5-20- The structural model of hypothesis 3-2. Bootstrapping test shows the path coefficient (T-statistics) of the moderation effect (i.e., Basis & Foundation * Location) between location driver and DPP.

Table 5-52 shows the factor loading and T-values of indicators belonging to the developed construct based on the definition of the sub-hypothesis 3-2. The acquired results were computed based on the bootstrapping test when the productivity approach was applied for the moderator (i.e., Basis & Foundation) variable. Although it seems this analysis has been conducted in the CFA section, it is necessary to check the factor loadings and T-values of all approved items by considering the sub-hypothesis 3-2 and its construct to ensure the reliability of the study has not been violated. It can be observed that the T-statistics of all indicators estimate the construct's stability, and all items' T-values have had satisfactory amounts higher than the defined threshold limit.

Table 5-52-Bootstrapping test (T-statistics) of hypothesis 3-2. The location driver and DPP are moderated by the Basis & Foundation.

	Factor Loading (O)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Bas2 <- Basis	0.796	0.256	3.111	0.002
Bas2 * Loc1 <- Basis* Location	0.819	0.056	14.591	0
Bas2 * Loc4 <- Basis* Location	0.817	0.055	14.73	0
Bas2 * Loc5 <- Basis* Location	0.812	0.058	13.975	0
Bas3 <- Basis	0.947	0.197	4.802	0
Bas3 * Loc1 <- Basis* Location	0.85	0.057	14.917	0
Bas3 * Loc4 <- Basis* Location	0.849	0.057	14.809	0
Bas3 * Loc5 <- Basis* Location	0.852	0.061	14.013	0
Bas6 <- Basis	0.863	0.247	3.492	0
Bas6 * Loc1 <- Basis* Location	0.776	0.06	12.911	0
Bas6 * Loc4 <- Basis* Location	0.771	0.06	12.757	0
Bas6 * Loc5 <- Basis* Location	0.772	0.061	12.65	0
Bas7 <- Basis	0.91	0.198	4.595	0
Bas7 * Loc1 <- Basis* Location	0.804	0.074	10.788	0
Bas7 * Loc4 <- Basis* Location	0.802	0.075	10.723	0
Bas7 * Loc5 <- Basis* Location	0.806	0.077	10.475	0
DPP2 <- DPP	0.856	0.029	29.39	0
DPP3 <- DPP	0.871	0.022	40.123	0
DPP6 <- DPP	0.822	0.032	25.473	0
DPP7 <- DPP	0.926	0.011	80.97	0

Loc1 <- Location	0.937	0.014	66.911	0
Loc4 <- Location	0.927	0.016	58.17	0
Loc5 <- Location	0.938	0.017	54.185	0

Table 5-53 shows the path coefficient and T-Statistic between two main variables (i.e., location driver & DPP), moderator (i.e., Basis & Foundation) and DPP, and moderation effect (i.e., Basis & Foundation * Location) and DDP at a 95% of confidence level. Both path coefficient (-0.135) and T-value (3.435) of the moderation effect were higher than threshold limits, and there is no zero between the lower and higher limit of confidence intervals. Hence, it can be concluded that the T-statistic of the moderation path between the Basis & Foundation * Location and DPP estimates the stability of the construct at the defined confidence interval. Thereby, it can be stated that the sub-hypothesis (H_{3-2}) has been approved statistically. However, the quality criteria of the developed construct have been checked to ensure the reliability and internal consistency of the construct have not been neglected.

Table 5-53-Path analysis of the hypothesis 3-2. The moderation effect of Basis & Foundation between location driver and DPP.

	Path Coefficient (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	LLCI (2.5%)	ULCI (97.5%)
Basis -> DPP	0.092	0.092	0.046	2.028	0.043	-0.016	0.174
Basis*Location -> DPP	-0.135	-0.142	0.039	3.435	0.001	-0.213	-0.064
Location -> DPP	0.889	0.887	0.022	39.928	0	0.841	0.927

Table 5-54 shows the quality criteria and discriminant validity based on the Fornell-Larcker criterion of sub-hypothesis 3-2. As explained in chapter 3 (see PLS-SEM path analysis), the square root of AVE would be higher than the correlation coefficient between the variables to satisfy the Fornell-Larcker criterion. The developed construct based on the definition of the third sub-hypothesis 3-2 has created an acceptable range of discriminant validity. In addition, it can be observed that all studied criteria, including CA, CR, and AVE, were higher than the defined threshold limits, which approved that the reliability, convergent validity, and internal

consistency of the developed construct for the third sub-hypothesis (3-3) and this sub hypothesis has been certified.

Table 5-54-Quality criteria of hypothesis 3-12 construct. The location driver and DPP are moderated by the Basis & Foundation.				
	Cronbach's Alpha (CA)	Composite Reliability (CR)	Average Variance Extracted (AVE)	R-squared
Basis	0.911	0.932	0.776	----
Basis*Location	0.964	0.968	0.717	---
DPP	0.892	0.925	0.756	0.817
Location	0.927	0.954	0.873	----

Discriminant validity of hypothesis 3-3 based on the Fornell-Larcker criterion.				
	Basis	Basis* Location	DPP	Location
Basis	0.881			
Basis*Location	0.279	0.847		
DPP	0.095	0.106	0.870	
Location	0.044	0.004	0.863	0.934

In conclusion, the bootstrapping test results showed that the sub-hypothesis (H3-2) research construct was fitted to the applied data. The relation between location driver and DPP has been moderated by the Basis & foundation, and therefore the sub-hypothesis (H_{3-2}) was supported.

5.9.3 Hypothesis 3-3: The relation between inventory driver and DPP is moderated by the Basis & Foundation

In this section, the relationship between inventory and DPP with the existence of the Basis & Foundation as a moderator was analysed. The indicators of the Basis & Foundation (as a moderator variable) were reported in the previous section after conducting CFA, including Bas 2, Bas 3, Bas 6, and Bas 7. Also, within the CFA, the inventory indicators were listed as Inv 2, Inv 4, Inv 5 and Inv 6. Figure 5-21 shows the path coefficients (O) and T-values of the developed construct based on the definition of the sub-hypothesis 3-3 using the productivity

approach by considering the moderation effect (Basis & Foundation * Inventory) between two variables (Inventory → DPP). The path coefficient (O) of moderation effect (i.e., Basis & Foundation * Inventory →DPP) was computed ($\beta = -0.117$ @ $\alpha < 0.05$) and the T-value was (3.002). The obtained path coefficient of the moderation effect is negative, which shows that there was a reverse correlation between the moderation effect and DPP. Although the path analysis's obtained T-value (3.002) was significant (higher than 1.96) using the bootstrapping test, it is necessary to conduct further analysis to investigate whether the indicators of moderation effect were accepted.

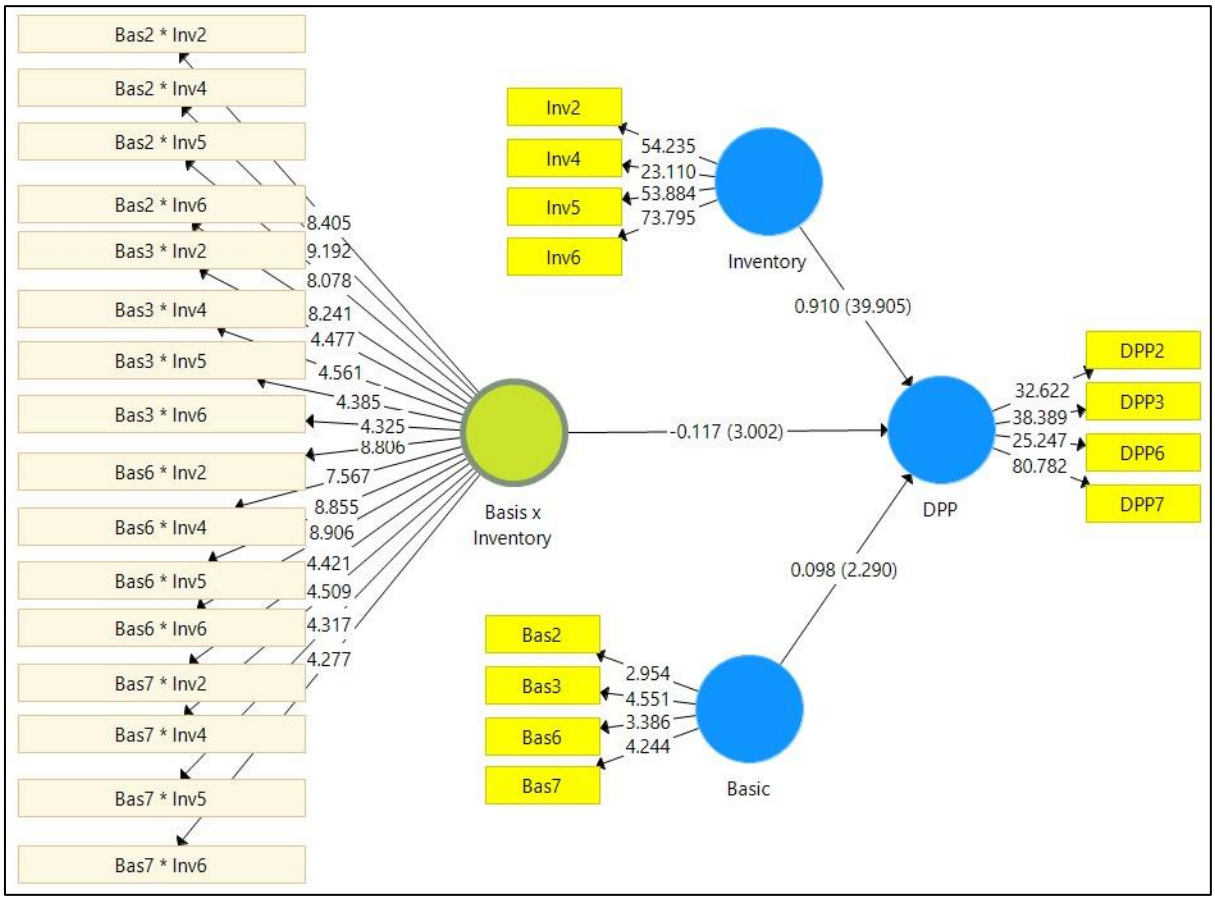


Figure 5-21- The structural model of sub-hypothesis 3-3. Bootstrapping calculation shows the path coefficient and (T-statistics) of the moderation effect (i.e., Basis & Foundation * Inventory) between inventory driver and DPP.

Table 5-55 shows the factor loading and T-values of indicators belonging to the developed construct based on the definition of sub-hypothesis 3-3. The acquired results were computed based on the bootstrapping test when the productivity approach was applied for the moderator (i.e., Basis & Foundation) variable. Although it seems this analysis has been conducted in the CFA section, it is necessary to check the factor loadings and T-values of all approved items

by considering the sub-hypothesis 3-3 and its construct to ensure the reliability of the study has not been violated. It can be observed that the T-statistics of all indicators estimate the construct's stability, and all items' T-values have had satisfactory amounts higher than the defined threshold limit.

Table 5-55-Bootstrapping calculation (T-statistics) of hypothesis 3-3. The inventory driver and DPP are moderated by the Basis & Foundation.

	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Bas2 <- Basis	0.732	0.269	2.954	0.003
Bas2 * Inv2 <- Basis* Inventory	0.715	0.09	8.405	0
Bas2 * Inv4 <- Basis* Inventory	0.714	0.081	9.192	0
Bas2 * Inv5 <- Basis* Inventory	0.716	0.094	8.078	0
Bas2 * Inv6 <- Basis* Inventory	0.73	0.094	8.241	0
Bas3 <- Basis	0.886	0.208	4.551	0
Bas3 * Inv2 <- Basis* Inventory	0.661	0.165	4.477	0
Bas3 * Inv4 <- Basis* Inventory	0.64	0.155	4.561	0
Bas3 * Inv5 <- Basis* Inventory	0.662	0.169	4.385	0
Bas3 * Inv6 <- Basis* Inventory	0.666	0.172	4.325	0
Bas6 <- Basis	0.791	0.255	3.386	0.001
Bas6 * Inv2 <- Basis* Inventory	0.699	0.081	8.806	0
Bas6 * Inv4 <- Basis* Inventory	0.695	0.092	7.567	0
Bas6 * Inv5 <- Basis* Inventory	0.706	0.082	8.855	0
Bas6 * Inv6 <- Basis* Inventory	0.715	0.083	8.906	0
Bas7 <- Basis	0.838	0.214	4.244	0
Bas7 * Inv2 <- Basis* Inventory	0.626	0.157	4.421	0
Bas7 * Inv4 <- Basis* Inventory	0.603	0.146	4.509	0
Bas7 * Inv5 <- Basis* Inventory	0.627	0.161	4.317	0
Bas7 * Inv6 <- Basis* Inventory	0.63	0.164	4.277	0
DPP2 <- DPP	0.861	0.026	32.622	0
DPP3 <- DPP	0.868	0.023	38.389	0
DPP6 <- DPP	0.82	0.033	25.247	0

DPP7 <- DPP	0.926	0.011	80.782	0
Inv2 <- Inventory	0.908	0.017	54.235	0
Inv4 <- Inventory	0.823	0.036	23.11	0
Inv5 <- Inventory	0.92	0.017	53.884	0
Inv6 <- Inventory	0.934	0.013	73.795	0

Table 5-56 shows the path coefficient and T-Statistic between two main variables (i.e., inventory driver & DPP), moderator (i.e., Basis & Foundation) and DPP, and moderation effect (i.e., Basis & Foundation * Inventory) and DDP at a 95% of confidence level. Both path coefficient (-0.117) and T-value (3.002) of the moderation effect were higher than threshold limits, and there is no zero between the lower and higher limit of confidence intervals. Hence, it can be concluded that the T-statistic of the moderation path between the Basis & Foundation * Inventory and DPP estimates the stability of the construct at the defined confidence interval. Thereby, it can be stated that the sub-hypothesis ($H_{3\text{-}3}$) has been approved statistically. However, the quality criteria of the developed construct have been checked to ensure the reliability and internal consistency of the construct have not been neglected.

Table 5-56-Path analysis of hypothesis 3-3. Inventory driver and DPP are moderated by the Basis & Foundation.

	Path Coefficient (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	LLCI (2.5%)	ULCI (97.5%)
Basis -> DPP	0.098	0.091	0.043	2.29	0.022	0.012	0.183
Basis* Inventory -> DPP	-0.117	-0.126	0.039	3.002	0.003	-0.189	-0.042
Inventory -> DPP	0.91	0.904	0.023	39.905	0	0.866	0.948

Table 5-57 demonstrates the quality criteria, including Cronbach's Alpha, CR, and AVE for the third sub-hypothesis (3-3). It can be observed that all criteria were higher than the defined threshold limits, which approved the reliability, convergent validity, and internal consistency of the developed construct for the third sub-hypothesis (3-3), and this sub-hypothesis has been certified.

Although the R-squared value would not be considered merely to evaluate the model's fitness in collected data, the R-squared value alongside the path coefficient and t-value can produce

a reasonable prediction about the developed sub-hypothesis model. R-squared has been computed and reported for the DPP variable to determine how the third sub-hypothesis (3-3) and its developed construct can strongly estimate the variance. By considering the T-Value (3.002) of the moderator path (Basis & Foundation * Inventory → DPP) at a 95% confidence interval and R-squared value (0.881), it can be concluded that the developed construct for the third sub-hypothesis ($H_{3\text{-}3}$) was fitted to the collected data and DPP can be explained 88.1% of the variance.

Table 5-57-Quality criteria of hypothesis 3-3. The inventory driver and DPP are moderated by the Basis & Foundation.

	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)	R-squared
Basis	0.911	0.932	0.776	----
Basis*Inventory	0.961	0.961	0.609	---
DPP	0.892	0.925	0.757	0.881
Inventory	0.918	0.943	0.805	----

Table 5-58 shows the discriminant validity based on the Fornell-Larcker criterion of sub hypothesis 3-3. As explained in chapter 3 for PLS-SEM path analysis, the square root of AVE would be higher than the correlation coefficient between the variables to satisfy the Fornell-Larcker criterion. The developed construct based on the definition of the third sub-hypothesis 3-3 has created an acceptable range of discriminant validity.

Table 5-58-Discriminant validity of hypothesis 3-3 based on the Fornell-Larcker criterion.

	Basis	Basis* Inventory	DPP	Inventory
Basis	0.881			
Basis*Inventory	0.24	0.78		
DPP	0.094	0.231	0.870	
Inventory	0.024	0.16	0.830	0.897

In conclusion, the quality criteria, discriminant validity, composite reliability, path coefficient, T-statistic, and R-squared values showed that the third sub-hypothesis (H3-3) research construct was fitted to the applied data. The relationship between inventory driver and DPP is moderated by the Basis & Foundation factor of the industrial clusters, and therefore the sub-hypothesis ($H_{3\text{-}3}$) is supported.

5.9.4 Hypothesis 3-5: The relation between information driver and DPP is moderated by the Basis & Foundation

In this section, the relationship between information and DPP with the existence of the Basis & Foundation as a moderator was analysed. The indicators of the Basis & Foundation (as a moderator variable) were reported in the previous section after conducting CFA, including Bas 2, Bas 3, Bas 6, and Bas 7. Also, within the CFA, the information indicators were listed as Inf 1, Inf 3, Inf 7, and Inf 8. Figure 5-22 shows the path coefficients (O) and T-values of the developed construct based on the definition of the sub-hypothesis 3-5 using the productivity approach by considering the moderation effect (Basis & Foundation * Information) between two variables (Information and DPP). The path coefficient (O) of the moderation effect (i.e., Basis & Foundation * Information →DPP) was computed ($\beta = -0.126$ @ $\alpha < 0.05$) and the t-value was (2.712). The obtained path coefficient of the moderation effect is negative, which shows a weak reverse correlation between the moderation effect and DPP. Although the path analysis's obtained t-value (2.712) was significant (higher than 1.96) using the bootstrapping test, it is necessary to conduct further analysis to investigate whether the T-values of indicators belonging to the moderation effect were accepted.

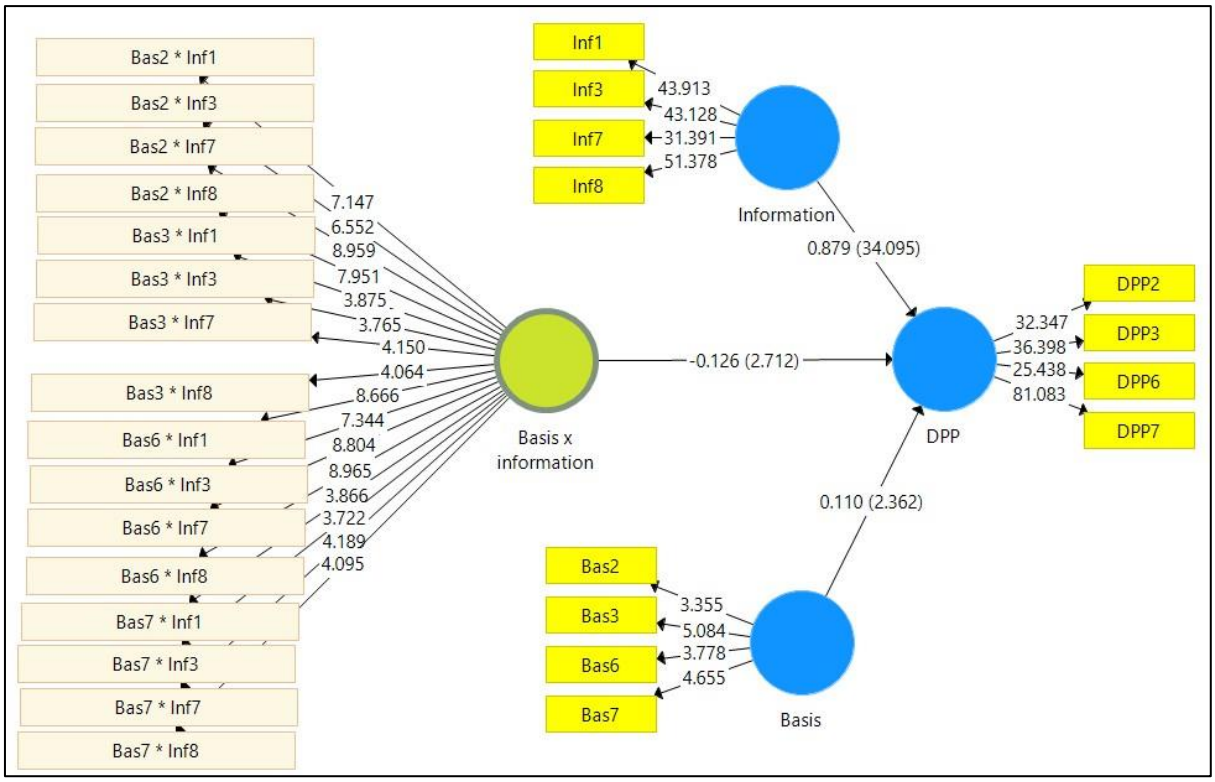


Figure 5-22- The structural model of sub-hypothesis 3-5. Bootstrapping calculation shows the path coefficient (T-statistics) of the moderation effect (i.e., Basis & Foundation * Information) between information driver and DPP.

Table 5-59 shows the factor loading and T-values of indicators belonging to the developed construct based on the definition of sub-hypothesis 3-5. The acquired results were computed based on the bootstrapping test when the productivity approach was applied for the moderator (i.e., Basis & Foundation) variable. Although it seems this analysis has been conducted in the CFA section, it is necessary to check the T-values of all approved items by considering the sub-hypothesis 3-5 and its construct to ensure the reliability of the study has not been violated. It can be observed that the T-statistics of all indicators estimate the construct's stability, and all items' T-values have had satisfactory amounts higher than the defined threshold limit.

Table 5-59-Factor loading and bootstrapping calculation (T-statistics) of hypothesis 3-5. The information driver and DPP are moderated by the Basis & Foundation.

	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Bas2 <- Basis	0.748	0.237	3.355	0.001
Bas2 * Inf1 <- Basis*information	0.718	0.107	7.147	0

Bas2 * Inf3 <- Basis*information	0.685	0.112	6.552	0
Bas2 * Inf7 <- Basis*information	0.724	0.084	8.959	0
Bas2 * Inf8 <- Basis*information	0.726	0.097	7.951	0
Bas3 <- Basis	0.896	0.186	5.084	0
Bas3 * Inf1 <- Basis*information	0.654	0.19	3.875	0
Bas3 * Inf3 <- Basis*information	0.626	0.189	3.765	0
Bas3 * Inf7 <- Basis*information	0.644	0.172	4.15	0
Bas3 * Inf8 <- Basis*information	0.655	0.181	4.064	0
Bas6 <- Basis	0.805	0.228	3.778	0
Bas6 * Inf1 <- Basis*information	0.717	0.085	8.666	0
Bas6 * Inf3 <- Basis*information	0.674	0.095	7.344	0
Bas6 * Inf7 <- Basis*information	0.714	0.081	8.804	0
Bas6 * Inf8 <- Basis*information	0.715	0.081	8.965	0
Bas7 <- Basis	0.847	0.195	4.655	0
Bas7 * Inf1 <- Basis*information	0.624	0.18	3.866	0
Bas7 * Inf3 <- Basis*information	0.593	0.18	3.722	0
Bas7 * Inf7 <- Basis*information	0.615	0.161	4.189	0
Bas7 * Inf8 <- Basis*information	0.627	0.17	4.095	0
DPP2 <- DPP	0.862	0.027	32.347	0
DPP3 <- DPP	0.864	0.024	36.398	0
DPP6 <- DPP	0.824	0.032	25.438	0
DPP7 <- DPP	0.925	0.011	81.083	0
Inf1 <- Information	0.908	0.021	43.913	0
Inf3 <- Information	0.895	0.021	43.128	0
Inf7 <- Information	0.877	0.028	31.391	0
Inf8 <- Information	0.911	0.018	51.378	0

Table 5-60 shows the path coefficient and T-Statistic between two main variables (i.e., information driver & DPP), moderator (i.e., Basis & Foundation) and DPP, and moderation effect (i.e., Basis & Foundation * Information) and DDP at a 95% of confidence level. The T-value (2.712) of the moderation effect was higher than threshold limits, and there is no zero between the lower and higher limit of confidence intervals. Hence, it can be concluded that the T-statistic of the moderation path between the Basis & Foundation * Information and DPP

estimates the stability of the construct at the defined confidence interval. Thereby, it can be stated that the sub-hypothesis (H_{3-5}) has been approved statistically. However, the quality criteria of the developed construct have been checked to ensure the reliability and internal consistency of the construct have not been neglected.

Table 5-60-Path analysis of hypothesis 3-5. The information driver and DPP are moderated by the Basis & Foundation.

	Path Coefficient (O)	Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Value	LLCI (2.5%)	ULCI (97.5%)
Basis -> DPP	0.11	0.104	0.047	2.362	0.018	0.011	0.194
Basis*information -> DPP	-0.126	-0.14	0.047	2.712	0.007	-0.21	-0.032
Information -> DPP	0.879	0.873	0.026	34.095	0	0.831	0.928

Table 5-61 demonstrates the quality criteria, including Cronbach's Alpha, CR, and AVE for the fifth sub-hypothesis (3-5). It can be observed that all criteria were higher than the defined threshold limits, which approved the reliability, convergent validity, and internal consistency of the developed construct for the third sub-hypothesis (3-5).

R-squared value of DPP has been computed and reported to determine how the fifth sub hypothesis (3-5) and its developed construct can strongly estimate the variance. By considering the T-Value (2.554) of the moderator path (Basis & Foundation * Information → DPP) at a 95% confidence interval and R-squared value (0.828), it can be concluded that the developed construct for the fifth sub-hypothesis (H_{3-5}) was fitted to the collected data and DPP can be explained 82.8% of the variance.

Table 5-61-Quality criteria of hypothesis 3-5. The information driver and DPP are moderated by the Basis & Foundation.

	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)	R-squared
Basis	0.911	0.932	0.776	----
Basis* information	0.962	0.962	0.615	---
DPP	0.892	0.925	0.757	0.828
Information	0.92	0.944	0.807	----

Table 5-62 shows the discriminant validity based on the Fornell-Larcker criterion of sub hypothesis 3-5. As explained in chapter 3 for PLS-SEM path analysis, the square root of AVE would be higher than the correlation coefficient between the variables to satisfy the Fornell-Larcker criterion. The information driver strongly relates to itself and the DPP factor, which certified the concept of sub-hypothesis 1-5. In addition, the developed construct based on the definition of the fifth sub-hypothesis 3-5 has created an acceptable range of discriminant validity.

Table 5-62-Discriminant validity of hypothesis 3-5 based on the Fornell-Larcker criterion.

	Basis	Basis* information	DPP	Information
Basis	0.881			
Basis*information	0.23	0.78		
DPP	0.096	0.23	0.87	
Information	0.01	0.16	0.801	0.898

In conclusion, the quality criteria, discriminant validity, composite reliability, path coefficient, T-statistic, and R-squared values were shown that the research construct of the fifth sub-hypothesis ($H_{3\text{-}5}$) was fitted to the applied data. The relationship between information driver and DPP is moderated by the Basis & Foundation factor of the industrial clusters, and therefore the sub-hypothesis ($H_{3\text{-}5}$) is supported.

5.10 Analysis of Hypothesis 4

This section must analyse the relationship between supply chain drivers and DPP with the existence of the Market factor as a moderator. The Market indicators (as a moderator variable) were determined in the CFA section, including Mark 1, Mark 4, Mark 5, and Mark 8. Figure 5-23 (a) and (b) show the path coefficients (O) and T-values of the fourth hypothesis model using two-stage and productivity approaches, respectively, by considering the moderation effect between two variables. In this analysis, the two-stage course has given a negative value of path coefficient (O) ($\beta = -0.082$ @ $\alpha < 0.05$) at significant T-value (2.229).

In contrast, the productivity technique has given a lower negative path coefficient ($\beta = -0.098$ @ $\alpha < 0.05$) at higher T-value (3.156). In this case, both approaches estimate the

negative path coefficients and significant T-values. Hence, there is no difference between the direction of the path analysis (both moderators were shown negative effect) and their obtained significant T-values (higher than 1.96).

As discussed previously, between the two-stage and productivity approaches, the two-stage method was applied in this study to determine the factor loadings and t-statistics of the indicators using the bootstrapping test (t-statistics). While the path analysis table is included the results of two-stage and productivity approaches using the bootstrapping test to ensure the fourth hypothesis has been appropriately analysed.

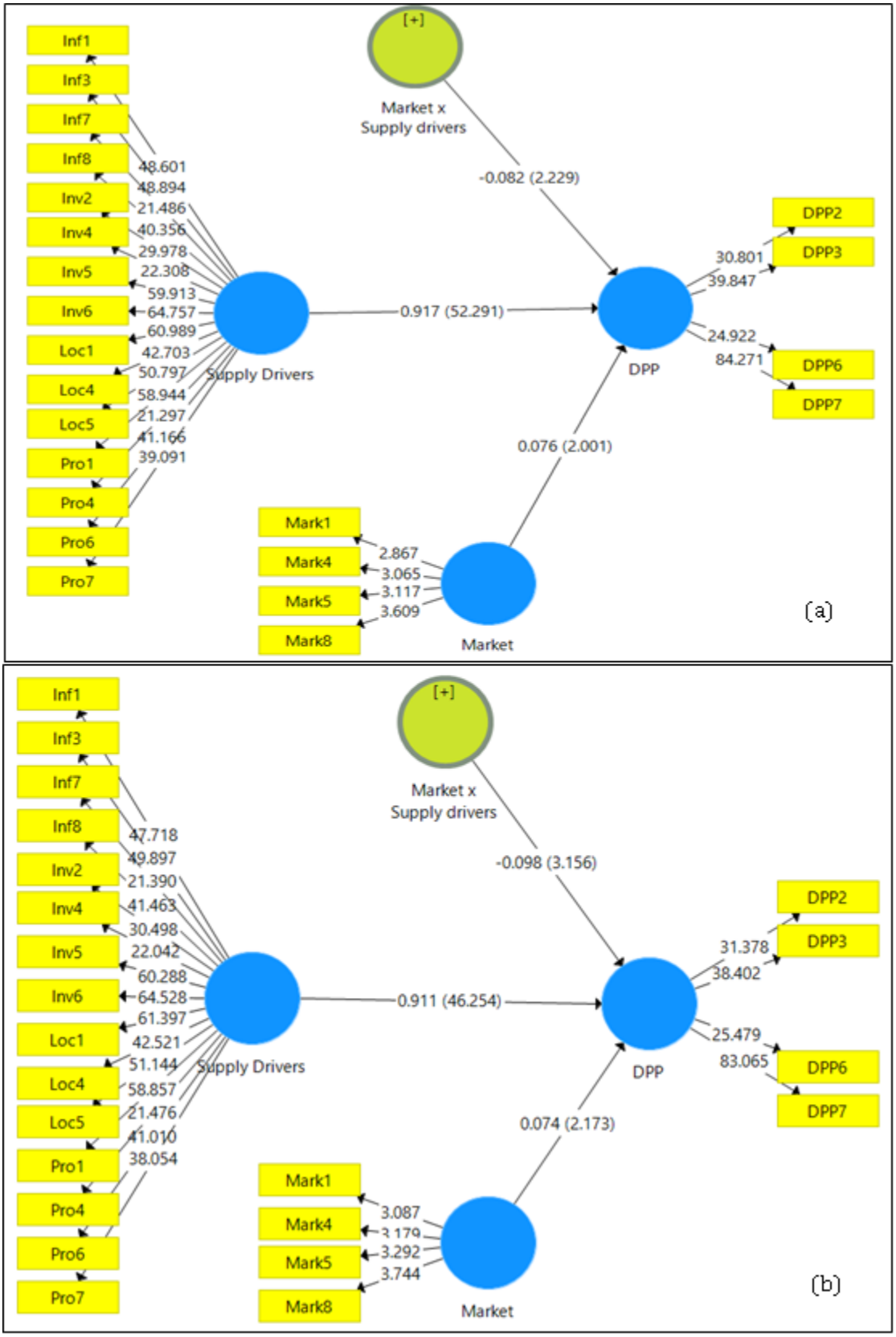


Figure 5-23- (a) shows the structural model of hypothesis 4 using two-stage technique and (b) using productivity approach for the moderation effect. Bootstrapping test has been used to determine the path coefficient (t-statistics).

Table 5-63 shows the factor loadings and T-values of indicators for the developed construct based on the definition of the fourth hypothesis. The acquired results were computed based on the bootstrapping test when the two-stage approach was applied for the moderator (i.e., market) variable. Although it seems this step has been conducted in the CFA section, it is necessary to check the factor loadings and T-values of all approved items by considering the fourth hypothesis and its construct to ensure the reliability of the study has not been violated. It can be observed that the factor loadings and T-statistics of all samples estimate the stability of the construct. Furthermore, factor loading of all indicators has had a satisfactory level higher than the threshold limit, proving that the fourth hypothesis was supported based on the collected data.

Table 5-63-Factor Loading (O) and bootstrapping calculation (T-statistics) of hypothesis 4. The moderation effect of the Market between supply chain drivers and DPP.

	Factor Loading (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
DPP2 <- DPP	0.859	0.858	0.028	30.801	0
DPP3 <- DPP	0.871	0.871	0.022	39.847	0
DPP6 <- DPP	0.819	0.818	0.033	24.922	0
DPP7 <- DPP	0.927	0.927	0.011	84.271	0
Inf1 <- Supply Drivers	0.903	0.903	0.019	48.601	0
Inf3 <- Supply Drivers	0.901	0.901	0.018	48.894	0
Inf7 <- Supply Drivers	0.809	0.809	0.038	21.486	0
Inf8 <- Supply Drivers	0.884	0.884	0.022	40.356	0
Inv2 <- Supply Drivers	0.85	0.85	0.028	29.978	0
Inv4 <- Supply Drivers	0.807	0.805	0.036	22.308	0
Inv5 <- Supply Drivers	0.927	0.927	0.015	59.913	0
Inv6 <- Supply Drivers	0.931	0.931	0.014	64.757	0
Loc1 <- Supply Drivers	0.93	0.93	0.015	60.989	0
Loc4 <- Supply Drivers	0.896	0.896	0.021	42.703	0
Loc5 <- Supply Drivers	0.909	0.909	0.018	50.797	0
Mark1 <- Market	0.813	0.735	0.284	2.867	0.004
Mark4 <- Market	0.759	0.69	0.248	3.065	0.002

Mark5 <- Market	0.837	0.762	0.269	3.117	0.002
Mark8 <- Market	0.859	0.782	0.238	3.609	0
Pro1 <- Supply Drivers	0.923	0.923	0.016	58.944	0
Pro4 <- Supply Drivers	0.816	0.816	0.038	21.297	0
Pro6 <- Supply Drivers	0.891	0.891	0.022	41.166	0
Pro7 <- Supply Drivers	0.897	0.897	0.023	39.091	0
Supply Drivers*Market <- Market*Supply drivers	0.942	0.961	0.083	11.317	0

Table 5-64 and Table 5-65 demonstrate outcomes of path analysis using bootstrapping test of the fourth hypothesis through two-stage and productivity approaches, respectively. The path coefficients (-0.082) between the moderation effect (Market*Supply drivers) and DPP is negatively moderated by the market variable using a two-stage approach. Also, the path coefficients (-0.098) between the moderation effect (Market*Supply drivers) and DPP is negatively moderated by the market variable using the productivity approach. Furthermore, the productivity approach computed a higher value of T-Statistic (3.156) rather than the two stage method (2.229). In this case, the T-Statistics of both directions in the presence of a market moderator were higher than the defined threshold limit. The higher T-Statistic value showed greater evidence against the null hypothesis and a significant difference in standard error units. On the other hand, there is a zero between LLCI (2.5%) and ULCI (97.5%) of the moderator factor when the two-stage approach has been used. The productivity approach produced satisfactory results as there is no zero between LLCI (2.5%) and ULCI (97.5%). Hence, it can be confirmed that the computed T- Statistics were valid at the 95% confidence interval when the productivity approach was used.

Table 5-64-Path analysis of hypothesis 4 **using a two-stage approach**. The moderation effect of the market between supply chain drivers and DPP.

	Path Coefficient (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Value	LLCI (2.5%)	ULCI (97.5%)
Market -> DPP	0.076	0.075	0.038	2.001	0.045	-0.026	0.136

Market*Supply drivers -> DPP	-0.082	-0.076	0.037	2.229	0.026	-0.143	-0.008
Supply Drivers -> DPP	0.917	0.917	0.018	52.291	0	0.877	0.946
Table 5-65-Path analysis of hypothesis 4 **using productivity approach**. The moderation effect of the market between supply chain drivers and DPP							
Market -> DPP	0.074	0.068	0.034	2.173	0.03	0.007	0.138
Market*Supply drivers -> DPP	-0.098	-0.106	0.031	3.156	0.002	-0.153	-0.025
Supply Drivers -> DPP	0.911	0.906	0.02	46.254	0	0.874	0.947

Table 5-66 demonstrates the quality criteria for the fourth hypothesis using a productive approach, including Cronbach's Alpha, CR, and AVE. It can be observed that all requirements were higher than defined threshold limits which approved that the reliability and internal consistency of the developed construct for the fourth hypothesis have been certified.

Although the R-squared value would not be considered merely to evaluate the model's fitness in collected data, considering the R-squared value alongside the path coefficient and T-value can generate a reasonable prediction about the hypothesis model. R-squared has been computed and reported for the DPP variable to determine how the fourth hypothesis and its developed construct can strongly estimate the variance. By considering the T-Value (3.609) of the moderator path (Market*Supply driver → DPP) at a 95% confidence interval and R-squared value (0.866), it can be concluded that the developed construct for the fourth hypothesis was fitted to the collected data and DPP can be explained 86.6% of the variance.

Table 5-66-Quality criteria of hypothesis 4 construct using productivity approach. The moderation effect of the market variable between supply chain drivers and DPP.

	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)	R-squared
DPP	0.892	0.925	0.756	0.866
Market	0.839	0.890	0.669	---
Market*Supply drivers	0.987	0.987	0.562	---
Supply Drivers	0.980	0.982	0.785	----

Table 5-67 shows the discriminant validity based on the Fornell-Larcker criterion of hypothesis 4. As explained in chapter 3 for PLS-SEM path analysis, the square root of AVE would be higher than the correlation coefficient between the variables to satisfy the Fornell-Larcker criterion. The developed construct based on the definition of the fourth hypothesis has created an acceptable range of discriminant validity.

Table 5-67-Discriminant validity of the structural model of hypothesis 4 using the productivity approach based on the Fornell-Larcker criterion.

	DPP	Market	Market*Supply drivers	Supply Drivers
DPP	0.870			
Market	0.084	0.818		
Market*Supply drivers	0.214	0.058	0.75	
Supply Drivers	0.824	0.014	0.144	0.886

In conclusion, the quality criteria, discriminant validity, composite reliability, path coefficient, T-statistic, and R-squared values were shown that the research construct of the fourth hypothesis (H_4) was fitted to the applied data. The relationship between supply chain drivers and DPP is moderated by the market factor of the industrial clusters, and therefore the fourth hypothesis (H4) is supported. However, suppose the interaction effect (i.e., Market*Supply drivers) exists between two variables in the presence of the moderator. In that case, it is required to complete the conducted analysis by drawing the interaction plots and applying SSA between variables to realise the direction of the moderation effect.

5.11 Simple slop analysis of H4

As discussed in chapter 3, section 3.10, it is necessary to complete the analysis of the moderation effect by considering the simple slop test (Dawson 2014).

Table 5-68 shows the steps of two-way linear interaction effects to plot the moderation effect via regression analysis. The values have been collected from the outcome of bootstrapping test using SmartPLS software (V3). Figure 5-24 shows the disordinal interaction effect of a moderator (i.e., Market * supply chain drivers) on the position of DPP.

The X-axis represents the independent variable (SC drivers), and Y-axis represents a dependent variable (DPP). The green line shows the effect of market moderation with a higher standard deviation (adding one SD unit to the mean value of the moderator), and the red line shows the effect of market moderation with a lower standard deviation (subtracting one SD unit from the mean value of moderator). Also, the blue line indicates the avenge effect of the market between supply chain drivers and DPP.

In this study, the moderator's higher effect (level) can be represented as a substantial effect on the market based on the validated measures in the CFA section. The lower moderation effect can be labelled as the weak effect of the market as a moderator. The stronger and weaker influence of the moderation effect indicated how the market could interact between the IV and DV in the industrial clusters. The difference between the higher and lower effects of the market depends on the value of SC drivers.

The slope of the green line indicated that the higher effect of the moderator increased the DPP value from -0.73 to 0.87 with the gradient of 0.8, while the slope of the lower effect of the market increased the value of DPP from -1.1 to 0.92 with the slope of 1.015. Hence, by considering the gradients between the two lines, the lower effect of the moderator (red line) has a more significant influence on the negative values of the DPP compared to the higher effect of the moderator. Moreover, a cross-over point (0.75, 0.68) occurred at the top-right corner of the graph, which shows moderator (i.e., market) has interacted between IV and DV at higher positive values rather than negative values of DPP. Furthermore, before the interaction effect (cross-over point), the position of the higher effect of the market (i.e., green line) was more significant than the lower effect of the moderator. While after the interaction point, the lower effect of the moderator (i.e., red line) was higher than the higher effect. Indeed, the interaction effect converted from a higher (green line) to a lower (red line) effect after the interaction point. Hence, this phenomenon shows that the lower effect of the moderator (red line) has a more significant impact on the SC driver values than the higher effect of the market (green line) after the cross-over point. In other words, the moderator has a minor negative impact on the SC driver after the interaction point where the SC driver has had higher values. This fact was matched with the obtained results of the negative path coefficient of the moderation effect (i.e., factor loading of Market* Supply drivers was -0.098).

Moreover, on the down-left corner of the graph (where the SC drivers and DPP have a negative value), there is a more significant variance between the higher and lower effect of the moderators ‘lines (i.e., a vertical gap between red and green lines). There is no vertical gap

between the red and green lines after the cross-over point (orange point in the graph), where the SC driver has a maximum positive value. It shows the variance between the higher and lower moderation effects was insignificant.

In conclusion, the simple slope analysis demonstrated that the interaction effect between moderator and DPP (i.e., Market* Supply drivers → DPP) has occurred within the defined standard deviations.

Table 5-68-The worksheet plots of two-way linear interaction effects via regression analysis (PLS and bootstrapping tests) to conduct simple slope analysis (adapted from (Dawson 2014).

Path Coefficients	**Values**
Independent variable (Supply Chain Drivers)	0.917
Moderator (Basis)	0.076
Interaction (Supply chain Drivers* Market)	-0.082
Dependent variable	DPP
Intercept / Constant	0
Means / SDs of variables:	**Values**
Mean of the independent variable	0.906
SD of the independent variable	0.020
Mean of moderator	0.068
SD of moderator	0.034

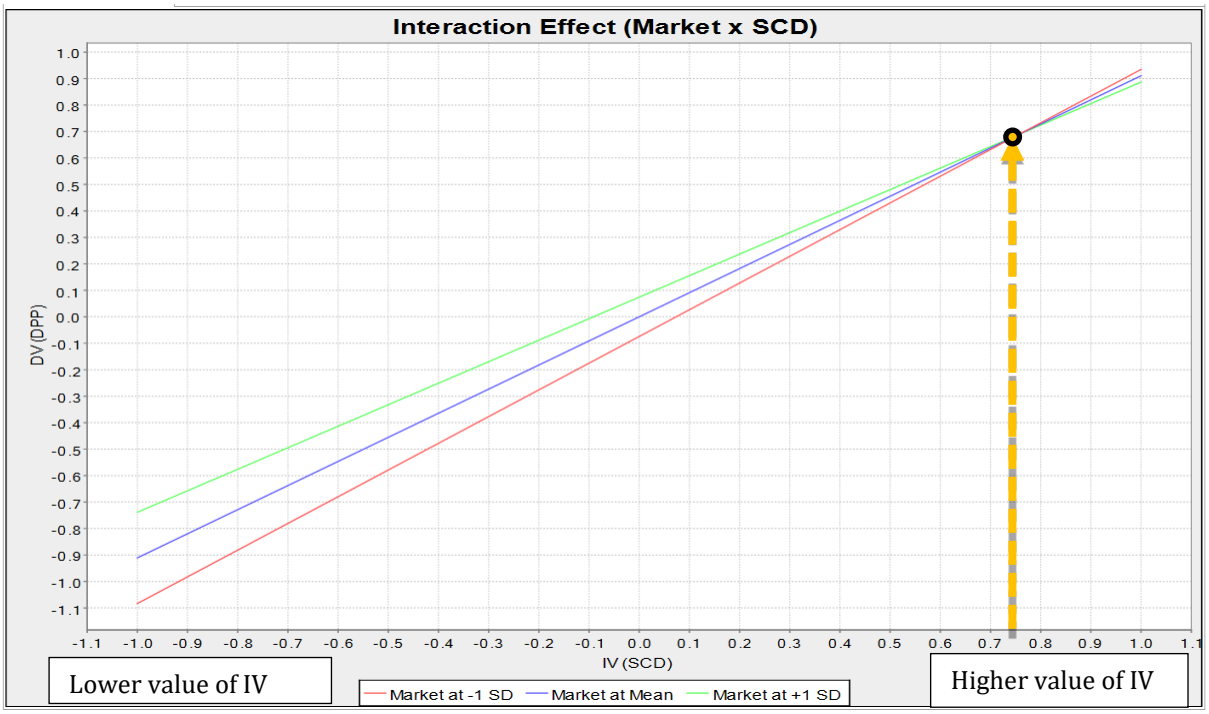


Figure 5-24- shows the simple slope analysis of the interaction effect (market*supply chain drivers) on the position of DPP related to the fourth hypothesis.

5.11.1 Hypothesis 4-1: The relationship between production driver and DPP is moderated by the Market

In this section, it is required to analyse the relationship between production and DPP with the existence of the Market factor as a moderator. The Market indicators (as a moderator variable) were determined in the CFA, including Mark 1, Mark 4, Mark 5, and Mark 8. Also, within the CFA, the production indicators were listed as Pro 1, Pro 4, Pro 6, and Pro 7. Figure 5-25 shows the path coefficients (O) and t-values of the sub-hypothesis model ($H_{4\text{-}1}$) using the productivity approach by considering the moderation effect between two variables (i.e., Production → DPP). The path coefficient (O) of the moderation effect (i.e., Market * Production) was computed ($\beta = -0.109$ @ $\alpha < 0.05$) and the t-value was (2.012). The obtained T-value was significant (higher than 1.96) using the bootstrapping test. The obtained path coefficient of the moderation effect is negative, which shows a reverse correlation between the moderation effect and DPP. In addition, the bootstrapping analysis showed that the moderator factor interacted between the production driver and DPP to develop the structural model based on the definition of the sub-hypothesis (4-1).

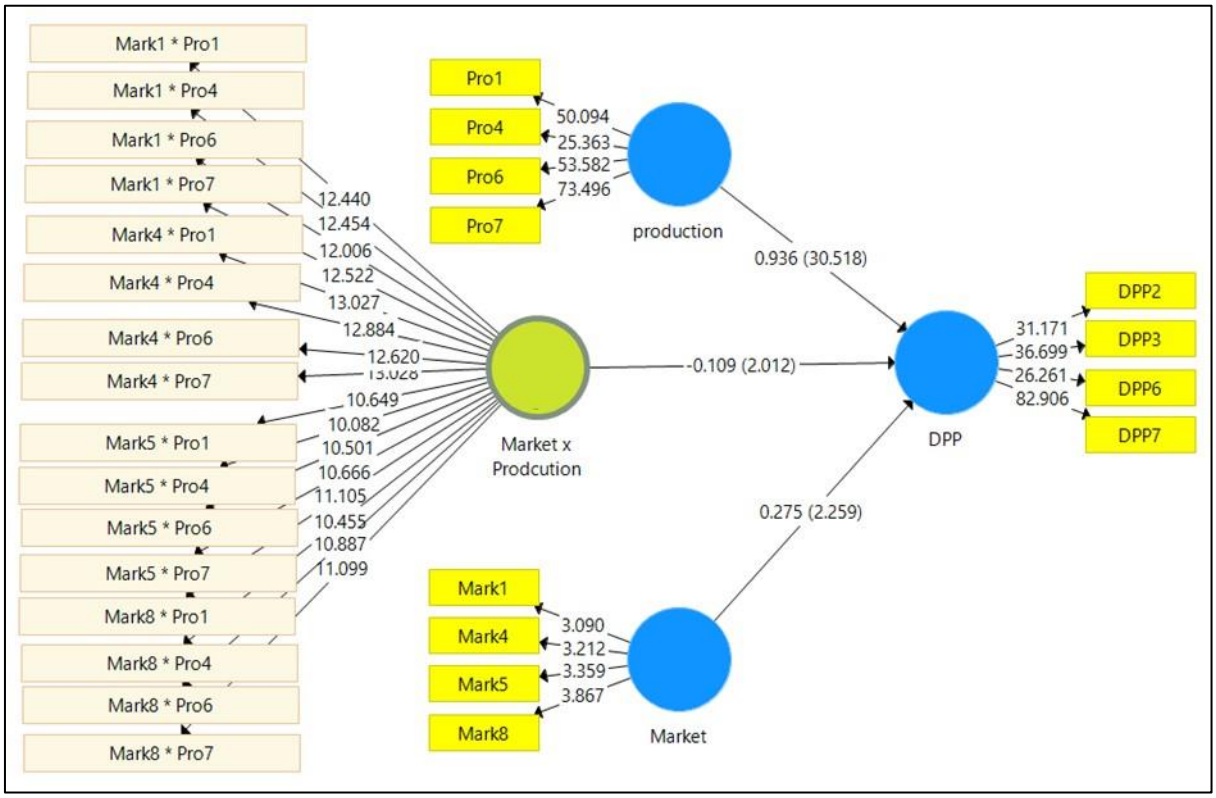


Figure 5-25-The structural model of sub-hypothesis 4-1. Bootstrapping analysis shows the path coefficient and (T-statistics) of the moderation effect (i.e., Market * Production) between production driver and DPP.

Table 5-69 shows the T-values and factor loadings of the indicators associated with the structural model of H_{4-1}. It can be observed that the factor loadings of all indicators belonging to the moderation effect were higher than the predefined value of 0.7. Furthermore, the obtained T-Statistics of the indicators belonging to the moderation effect (i.e., Basis & Foundation * production) were higher than the satisfactory limit ($|\pm 1.96|$). Hence, it might be concluded that the indicators of moderation effect (Basis & Foundation * production) interacted significantly between the production driver and DPP.

Table 5-69-Bootstrapping calculation (T-statistics) of hypothesis 4-1. The Market variable moderates the production driver and DPP.

	Factor Loading (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
DPP2 <- DPP	0.86	0.86	0.028	31.171	0
DPP3 <- DPP	0.866	0.867	0.024	36.699	0
DPP6 <- DPP	0.825	0.823	0.031	26.261	0
DPP7 <- DPP	0.925	0.926	0.011	82.906	0
Mark1 <- Market	0.816	0.743	0.264	3.09	0.002
Mark1*Pro1 <- Market*Production	1.769	1.759	0.142	12.44	0
Mark1*Pro4 <- Market*Production	1.699	1.684	0.136	12.454	0
Mark1*Pro6 <- Market*Production	1.76	1.752	0.147	12.006	0
Mark1*Pro7 <- Market*Production	1.773	1.762	0.142	12.522	0
Mark4 <- Market	0.758	0.696	0.236	3.212	0.001
Mark4*Pro1 <- Market*Production	1.67	1.654	0.128	13.027	0
Mark4*Pro4 <- Market*Production	1.638	1.619	0.127	12.884	0
Mark4*Pro6 <- Market*Production	1.653	1.637	0.131	12.62	0
Mark4*Pro7 <- Market*Production	1.678	1.661	0.129	13.028	0
Mark5 <- Market	0.839	0.771	0.25	3.359	0.001
Mark5*Pro1 <- Market*Production	1.77	1.768	0.166	10.649	0
Mark5*Pro4 <- Market*Production	1.715	1.705	0.17	10.082	0
Mark5*Pro6 <- Market*Production	1.758	1.759	0.167	10.501	0
Mark5*Pro7 <- Market*Production	1.776	1.772	0.167	10.666	0
Mark8 <- Market	0.857	0.79	0.222	3.867	0

Mark8*Pro1 <- Market*Production	1.711	1.704	0.154	11.105	0
Mark8*Pro4 <- Market*Production	1.676	1.663	0.16	10.455	0
Mark8*Pro6 <- Market*Production	1.695	1.69	0.156	10.887	0
Mark8*Pro7 <- Market*Production	1.719	1.71	0.155	11.099	0
Pro1 <- production	0.907	0.907	0.018	50.094	0
Pro4 <- production	0.849	0.848	0.033	25.363	0
Pro6 <- production	0.915	0.916	0.017	53.582	0
Pro7 <- production	0.934	0.934	0.013	73.496	0

Table 5-70 shows the path coefficient and T-Statistic between two main variables (i.e., production driver & DPP), moderator (i.e., Market) and DPP, and moderation effect (i.e., Market * production) and DDP at a 95% of confidence level. The path coefficient (-0.109) was negative at a significant T-value (2.012) of the moderation effect, which was higher than the threshold limit. Hence, it can be concluded that the T-statistic of the moderation path between the market * production and DPP did estimate the stability of the construct at the defined confidence interval. In addition, for the moderator factor, the T-value of the moderator factor (2.259 @ P-value>0.05) were higher than $|\pm 1.96|$ and therefore, the path analysis of the moderation effect supported the sub-hypothesis 4-1.

Table 5-70-Path analysis of hypothesis 4-1. The Market variable moderates the production driver and DPP.

	Path Coefficient (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics |O/STDEV|	P-Value	Supported (Yes/No)
Market -> DPP	0.275	0.221	0.122	2.259	0.024	Yes
Market*Production -> DPP	-0.109	-0.085	0.054	2.012	0.044	
Production -> DPP	0.936	0.922	0.031	30.518	0	

Table 5-71 demonstrates the quality criteria, including Cronbach's Alpha, CR, and AVE for the sub-hypothesis 4-1. It can be observed that all requirements were higher than defined threshold limits which approved the reliability and internal consistency of the developed construct for the sub-hypothesis (4-1), and this sub-hypothesis has been certified.

Although the R-squared value would not be considered merely to evaluate the model's fitness for the collected data, considering the R-squared value alongside the path coefficient and T-value can produce a reasonable prediction about the hypothesis model. R-squared has been computed and reported for the DPP variable to determine how the sub-hypothesis 4-1 and its developed construct can strongly estimate the variance. By considering the T-Value (2.012) of the moderator path (market * production → DPP) at a 95% confidence interval and R-squared value (0.797), it can be concluded that the developed construct for the sub-hypothesis (H_{4-1}) was fitted to the collected data and DPP can be explained 79.7% of the variance.

Table 5-71-Quality criteria of hypothesis 4-1 construct. The market variable moderates the production driver and DPP.

	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)	R-squared
DPP	0.892	0.925	0.757	0.797
Market	0.839	0.890	0.669	---
Market * Production	0.96	0.964	0.623	---
Production	0.923	0.946	0.814	----

Table 5-72 shows the discriminant validity based on the Fornell-Larcker criterion of sub hypothesis 4-1. As explained in chapter 3 for PLS-SEM path analysis, the square root of AVE would be higher than the correlation coefficient between the variables to satisfy the Fornell-Larcker criterion. The developed construct based on the definition of the sub- hypothesis 4-1 has created an acceptable range of discriminant validity.

Table 5-72-Discriminant validity of hypothesis 4-1 based on the Fornell-Larcker criterion.

	DPP	Market	Market * Production	production
DPP	0.87			
Market	0.083	0.818		
Market * Production	0.238	0.815	0.789	
Production	0.858	0.027	0.239	0.902

In conclusion, the quality criteria, discriminant validity, composite reliability, path coefficient, T-statistic, and R-squared values were shown that the research construct of the fourth sub-hypothesis (H_{4-1}) was fitted to the applied data. The relationship between production and DPP is moderated by the market factor of the industrial clusters, and therefore the fourth sub-hypothesis (H_{4-1}) is supported.

5.11.2 Hypothesis 4-2: The relationship between location driver and DPP is moderated by the Market

In this section, the relationship between location and DPP with the existence of the Market as a moderator was analysed. The market indicators were reported in the previous quarter after conducting CFA, including Mark 1, Mark 4, Mark 5, and Mark 8. Also, within the CFA, the location indicators were listed as Loc 1, Loc 4, and Loc 5.

Figure 5-26 shows the path coefficients (O) and T-values of the developed construct based on the definition of the sub hypothesis 4-2 using the productivity approach by considering the moderation effect between two variables (Location → DPP).

The path coefficient (O) of the moderation effect (i.e., Market * Location → DPP) was computed ($\beta = -0.140$ @ $\alpha < 0.05$) and the T-value was (3.025). The obtained path coefficient of the moderation effect is negative, which shows that there was a reverse correlation between the moderation effect and DPP.

Although the path analysis of the obtained t-value (3.025) was significant (higher than 1.96) using the bootstrapping test, it is necessary to conduct further research to investigate whether the indicators of the moderation effect were accepted.

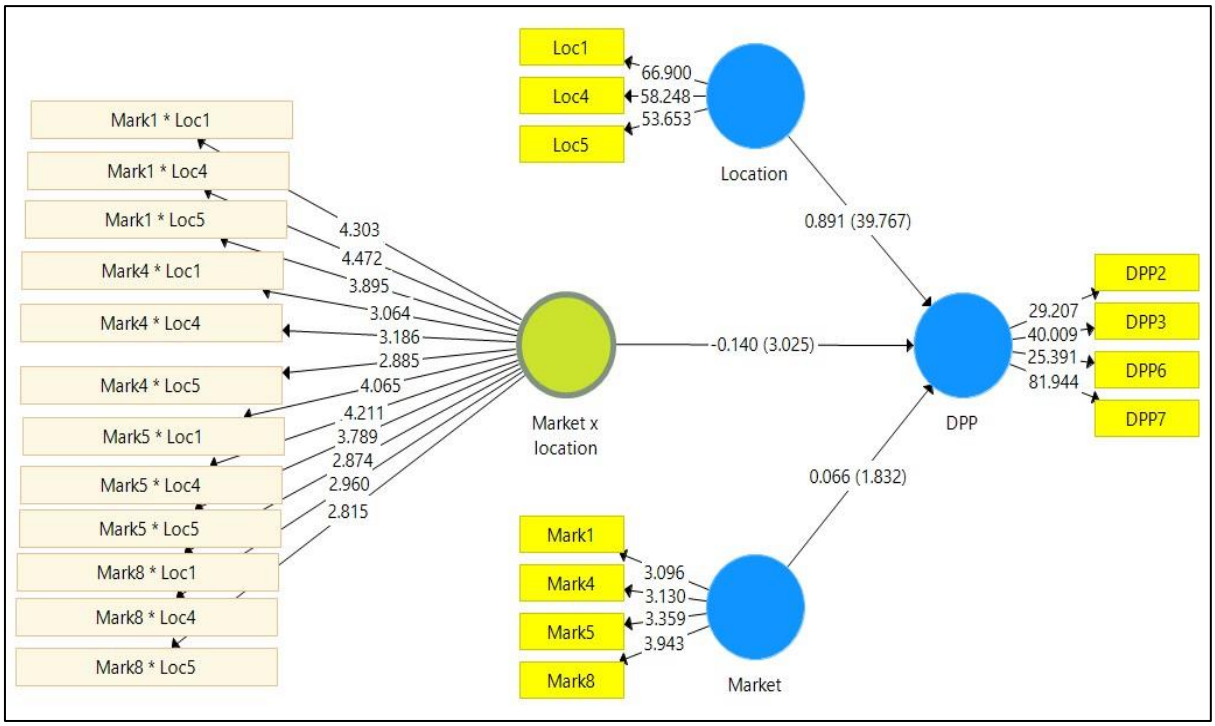


Figure 5-26-The structural model of sub-hypothesis 4-2. Bootstrapping analysis shows the path coefficient (T-statistics) of the moderation effect (i.e., Market) between location driver and DPP.

Table 5-73 shows the T-values and factor loadings of the indicators associated with the structural model of $H_{4\text{-}2}$. It can be observed that the factor loadings of six items belonging to the moderation effect were lower than the predefined value of 0.7. Hence, it can be stated that these indicators of moderation effect (market * production) did not interact significantly between production drivers and DPP. However, the following table conducted the path analysis to ensure the indicators are associated with the construct.

Table 5-73-Bootstrapping calculation (T-statistics) of hypothesis 4-2. The market variable moderates the location driver and DPP.

	Factor Loading (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics |O/STDEV|	P Values
DPP2 <- DPP	0.856	0.855	0.029	29.207	0
DPP3 <- DPP	0.871	0.871	0.022	40.009	0
DPP6 <- DPP	0.822	0.82	0.032	25.391	0
DPP7 <- DPP	0.927	0.926	0.011	81.944	0
Loc1 <- Location	0.937	0.937	0.014	66.90	0

Loc4 <- Location	0.927	0.927	0.016	58.248	0
Loc5 <- Location	0.938	0.938	0.017	53.653	0
Mark1 <- Market	0.815	0.743	0.263	3.096	0.002
Mark1*Loc1 <- Market * location	0.790	0.734	0.184	4.303	0
Mark1*Loc4 <- Market * location	0.790	0.739	0.177	4.472	0
Mark1*Loc5 <- Market * location	0.766	0.704	0.197	3.895	0
Mark4 <- Market	0.758	0.696	0.242	3.130	0.002
Mark4*Loc1 <- Market * location	0.673	0.61	0.22	3.064	0.002
Mark4*Loc4 <- Market * location	0.679	0.619	0.213	3.186	0.001
Mark4*Loc5 <- Market * location	0.665	0.594	0.23	2.885	0.004
Mark5 <- Market	0.839	0.772	0.25	3.359	0.001
Mark5*Loc1 <- Market * location	0.751	0.696	0.185	4.065	0
Mark5*Loc4 <- Market * location	0.755	0.702	0.179	4.211	0
Mark5*Loc5 <- Market * location	0.740	0.675	0.195	3.789	0
Mark8 <- Market	0.858	0.789	0.218	3.943	0
Mark8*Loc1 <- Market * location	0.674	0.616	0.235	2.874	0.004
Mark8*Loc4 <- Market * location	0.680	0.623	0.23	2.960	0.003
Mark8*Loc5 <- Market * location	0.672	0.604	0.239	2.815	0.005

Table 5-74 demonstrates the path coefficient and T-Statistic of the pathway between three variables of the developed construct, including location, DPP, and market. The moderation effect has been defined as a location * market, which is the main part of the structural model based on the definition of sub-hypothesis (4-2). The T-Statistic value between moderator and DPP (ß=0.066, T: 1.832, 95%, CI [-0.016, 0.130], @ P-value < 0.05). The existence of zero between the LLCI and ULCI leads to the rejection of the path coefficient and T-value of the Market → DPP. Comparably, the T-value between moderation effect and DPP (Market*location →DPP) was 3.321@ P-value < 0.05. On the other hand, the obtained T-statistic of the moderation effect was higher than|±1.96| and there is no zero between the LLCI and ULCI. In conclusion, it can be stated there is no significant effect between the moderator and DPP, and therefore sub-hypothesis 4-2 were rejected.

Table 5-74-Path analysis of hypothesis 4-2. The market variable moderates the location driver and DPP.						
	Path Coefficient (O)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Value	LLCI (2.5%)	ULCI (97.5%)
Location -> DPP	0.891	0.022	39.767	0	0.838	0.926
Market -> DPP	0.066	0.036	1.832	0.067	-0.016	0.130
Market*location -> DPP	-0.140	0.046	3.025	0.002	-0.228	-0.030

Table 5-75 demonstrates the quality criteria, including Cronbach's Alpha, CR, and AVE for the sub-hypothesis 4-2. It can be observed that all criteria were higher than defined threshold limits which approved the reliability and internal consistency of the developed construct. However, due to obtaining the unsatisfactory values of the T-Statistic and path coefficient of the moderator, the sub-hypothesis 4-2 was not proved.

Table 5-75-Quality criteria of hypothesis 4-2 construct. The market variable moderates the location driver and DPP.				
	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)	R-squared
DPP	0.892	0.925	0.756	0.817
Location	0.927	0.954	0.873	---
Market	0.839	0.890	0.669	---
Market * location	0.956	0.960	0.669	---

Concerning acquiring the unsatisfactory values of the T-test, path coefficient, P-value, and the LLCI and ULCI belonging to the moderator effect (Market →DPP), the sub-hypothesis 4-2 was not proved. Hence, it is unnecessary to investigate the discriminant validity of sub hypothesis (4-2) based on the Fornell-Larcker criterion.

In conclusion, the bootstrapping test results showed that the sub-hypothesis (H4-2) research construct was not fitted to the applied data. The market has not moderated the relation between location driver and DPP; therefore, the sub-hypothesis (H_{4-2}) was not supported.

5.11.3 Hypothesis 4-3: The relationship between inventory driver and DPP is moderated by the Market

The relationship between location and DPP with the existence of the market as a moderator was analysed in this section. After conducting CFA, the previous section reported the market indicators, including Mark 1, Mark 4, Mark 5, and Mark 8. Also, within the CFA, the location indicators were listed as Inv 2, Inv 4, Inv 5 and Inv 6. Figure 5-27 shows the path coefficients (O) and T-values of the developed construct based on the definition of the sub-hypothesis 43 using the productivity approach by considering the moderation effect between two variables (Location → DPP). The path coefficient (O) of the moderation effect (i.e., Market * Inventory → DPP) was computed ($\beta = -0.102$ @ $\alpha < 0.05$) and the T-value was (3.339). The obtained path coefficient of the moderation effect is negative, which shows that there was a reverse correlation between the moderation effect and DPP. Although the path analysis's obtained T-value (3.339) was significant (higher than 1.96) using the bootstrapping test, it is necessary to conduct further analysis to investigate whether the indicators of moderation effect were accepted.

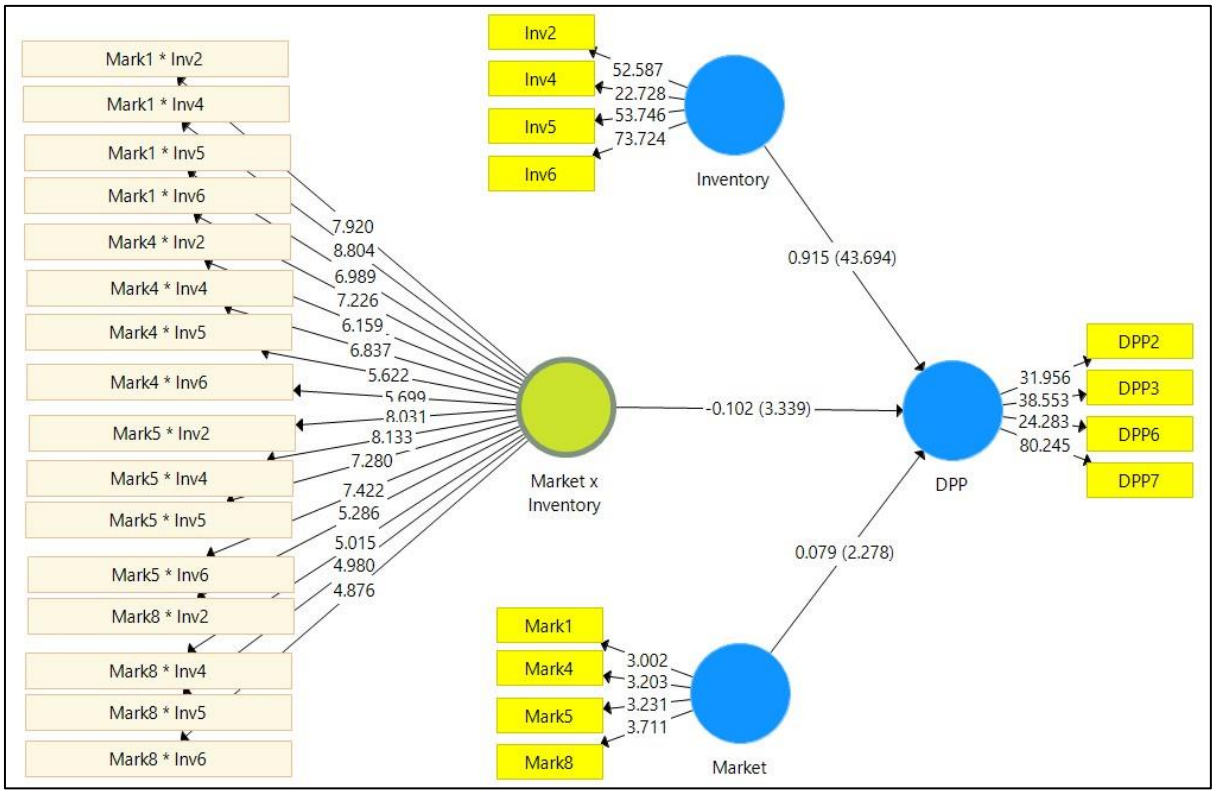


Figure 5-27- The structural model of sub-hypothesis 4-3. Bootstrapping analysis shows the path coefficient and (T-statistics) of the moderation effect (i.e., Market * Location) between inventory driver and DPP.

Table 5-76 shows the T-values and factor loadings of the indicators associated with the structural model of $H_{4\text{-}3}$. It can be observed that the factor loadings of all items belonging to the moderation effect were higher than the threshold limit of 0.7. Furthermore, the obtained T-Statistics of these indicators belonging to the moderation effect (i.e., market * production) were higher than the satisfactory limit ($|\pm 1.96|$). Hence, it can be concluded that these indicators of moderation effect (market * production) interacted significantly between production drivers and DPP.

Table 5-76-Bootstrapping test (T-statistics) of hypothesis 4-3. The market variable moderates the inventory driver and DPP.

	Factor Loading (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
DPP2 <- DPP	0.861	0.861	0.027	31.956	0
DPP3 <- DPP	0.869	0.87	0.023	38.553	0
DPP6 <- DPP	0.82	0.819	0.034	24.283	0
DPP7 <- DPP	0.926	0.926	0.012	80.245	0
Inv2 <- Inventory	0.907	0.907	0.017	52.587	0
Inv4 <- Inventory	0.824	0.823	0.036	22.728	0
Inv5 <- Inventory	0.92	0.92	0.017	53.746	0
Inv6 <- Inventory	0.934	0.934	0.013	73.724	0
Mark1 <- Market	0.813	0.741	0.271	3.002	0.003
Mark1*Inv2 <- Market*Inventory	0.689	0.668	0.087	7.92	0
Mark1*Inv4 <-Market*Inventory	0.663	0.669	0.075	8.804	0
Mark1*Inv5 <- Market*Inventory	0.694	0.666	0.099	6.989	0
Mark1 * Inv6 <- Market*Inventory	0.704	0.677	0.097	7.226	0
Mark4 <- Market	0.758	0.696	0.237	3.203	0.001
Mark4 * Inv2 <- Market*Inventory	0.639	0.609	0.104	6.159	0
Mark4 * Inv4 <- Market*Inventory	0.601	0.593	0.088	6.837	0
Mark4 * Inv5 <- Market*Inventory	0.636	0.601	0.113	5.622	0
Mark4 * Inv6 <- Market*Inventory	0.64	0.607	0.112	5.699	0
Mark5 <- Market	0.838	0.767	0.259	3.231	0.001
Mark5 * Inv2 <- Market*Inventory	0.687	0.658	0.086	8.031	0

Mark5 * Inv4 <- Market*Inventory	0.651	0.648	0.08	8.133	0
Mark5 * Inv5 <- Market*Inventory	0.69	0.655	0.095	7.28	0
Mark5 * Inv6 <- Market*Inventory	0.692	0.66	0.093	7.422	0
Mark8 <- Market	0.859	0.785	0.231	3.711	0
Mark8 * Inv2 <- Market*Inventory	0.643	0.611	0.122	5.286	0
Mark8 * Inv4 <- Market*Inventory	0.598	0.589	0.119	5.015	0
Mark8 * Inv5 <- Market*Inventory	0.642	0.606	0.129	4.98	0
Mark8 * Inv6 <- Market*Inventory	0.64	0.606	0.131	4.876	0

Table 5-77 shows the path coefficient and T-Statistic between two main variables (i.e., inventory driver & DPP), moderator (i.e., market) and DPP, and moderation effect (i.e., market * inventory) and DDP at a 95% of confidence level. Both path coefficient (--0.102) and T-value (3.339) of the moderation effect were higher than threshold limits, and there is no zero between the lower and higher limit of confidence intervals. Hence, it can be concluded that the T-statistic of the moderation path between the market * inventory and DPP estimates the stability of the construct at the defined confidence interval. Thereby, it can be stated that the sub-hypothesis (H_{4-3}) has been approved statistically. However, the quality criteria of the developed construct have been checked to ensure the reliability and internal consistency of the construct have not been neglected.

Table 5-77-Path analysis of hypothesis 4-3. The market variable moderates the inventory driver and DPP.

	Path Coefficient (O)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Value	LLCI (2.5%)	ULCI (97.5%)
Inventory -> DPP	0.915	0.021	43.694	0	0.865	0.946
Market -> DPP	0.079	0.034	2.278	0.023	-0.004	0.135
Market*Inventory -> DPP	C	0.03	3.339	0.001	-0.173	-0.055

Table 5-78 demonstrates the quality criteria for the sub-hypothesis, including Cronbach's Alpha, CR, and AVE. It can be observed that all requirements were higher than defined threshold limits which approved that the reliability and internal consistency of the developed construct for the sub-hypothesis (4-3) have been certified. Although the R-squared value would not be considered merely to evaluate the model's fitness in collected data, considering

the R-squared value alongside the path coefficient and T-value can produce a reasonable prediction about the hypothesis model. R-squared has been computed and reported for the DPP variable to determine how the sub-hypothesis and its developed construct can estimate the variance. By considering the T-Value (3.339) of the moderator path (market * production → DPP) at a 95% confidence interval and R-squared value (0.878), it can be concluded that the developed construct for the sub-hypothesis (H_{4-3}) was fitted to the collected data and DPP can be explained 87.8% of the variance.

Table 5-78-Quality criteria of hypothesis 4-3 construct. The market variable moderates the location driver and DPP.

	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)	R-Squared
DPP	0.892	0.925	0.756	0.878
Inventory	0.918	0.943	0.805	---
Market	0.839	0.89	0.669	---
Market*Inventory	0.95	0.953	0.559	---

Table 5-79 shows the discriminant validity based on the Fornell-Larcker criterion of sub hypothesis 4-3. As explained in chapter 3 for PLS-SEM path analysis, the square root of AVE would be higher than the correlation coefficient between the variables to satisfy the Fornell-Larcker criterion. The developed construct based on the definition of the third sub-hypothesis 4-3 has created an acceptable range of discriminant validity.

Table 5-79-Discriminant validity of hypothesis 4-3 construct based on the Fornell-Larcker criterion.

	DPP	Inventory	Market	Market*Inventory
DPP	0.881			
Inventory	0.830	0.897		
Market	0.084	0.007	0.818	
Market*Inventory	0.23	0.158	0.042	0.748

In conclusion, the quality criteria, discriminant validity, composite reliability, path coefficient, T-statistic, and R-squared values showed that the third sub-hypothesis (H4-3) research

construct was fitted to the applied data. The market factor moderates the relationship between inventory driver and DPP for the industrial clusters, and therefore, the sub-hypothesis (H_{4-3}) is supported.

5.11.4 Hypothesis 4-5: The relationship of information driver and DPP is moderated by the Market

The relationship between information and DPP with the existence of the market as a moderator was analysed in this section. The market indicators (as a moderator variable) were reported in the previous section after conducting CFA, including Mark 1, Mark 4, Mark 5, and Mark 8. Also, within the CFA, the information indicators were listed as Inf 1, Inf 3, Inf 7, and Inf 8. Figure 5-28 shows the path coefficients (O) and T-values of the developed construct based on the definition of the sub-hypothesis 4-5 using the productivity approach by considering the moderation effect (market* information) between the two variables (information and DPP). The path coefficient (O) of the moderation effect (i.e., market * information →DPP) was computed ($\beta = -0.102$ @ $\alpha < 0.05$) and the T-value was (2.682). The obtained path coefficient of the moderation effect is negative, which shows a weak reverse correlation between the moderation effect and DPP. Although the path analysis's obtained T-value (2. 682) was significant (higher than 1.96) using the bootstrapping test, it is necessary to conduct further analysis to investigate whether the T-values of indicators belonging to the moderation effect were accepted.

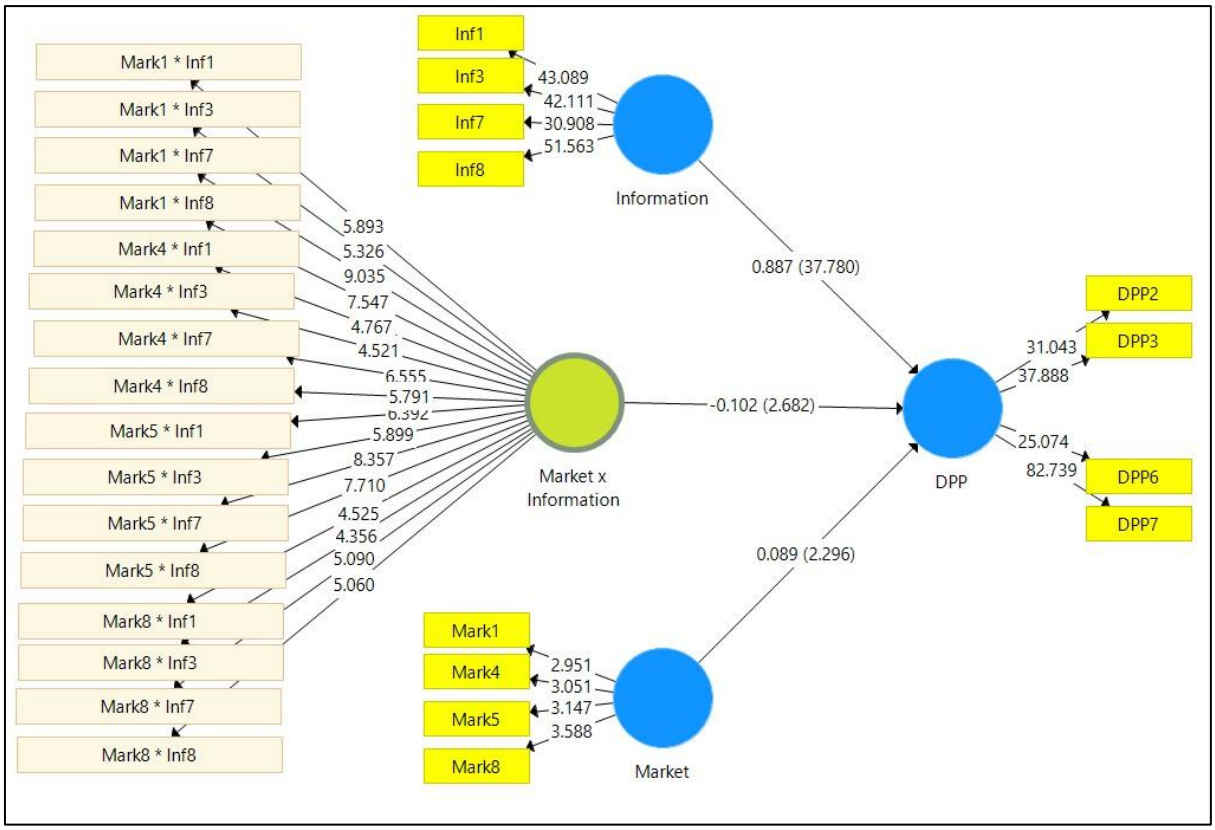


Figure 5-28-The structural model of sub-hypothesis 4-5. Bootstrapping analysis shows the path coefficient (T-statistics) of the moderation effect (i.e., market * information) between information driver and DPP.

Table 5-80 shows the T-values and factor loadings of the indicators associated with the structural model of $H_{4\text{-}5}$. It can be observed that the factor loadings of all items belonging to the moderation effect were higher than the threshold limit of 0.7. Furthermore, the obtained T-Statistics of these indicators belonging to the moderation effect (i.e., market * production) were higher than the satisfactory limit (|±1.96|). Hence, it can be concluded that these indicators of moderation effect (market * production) interacted significantly between production drivers and DPP.

Table 5-80-Bootstrapping test (T-statistics) of hypothesis 4-5. The market variable moderates the information driver and DPP.

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
DPP2 <- DPP	0.861	0.86	0.028	31.043	0
DPP3 <- DPP	0.868	0.869	0.023	37.888	0
DPP6 <- DPP	0.821	0.819	0.033	25.074	0

DPP7 <- DPP	0.926	0.926	0.011	82.739	0
Inf1 <- Information	0.909	0.908	0.021	43.089	0
Inf3 <- Information	0.895	0.895	0.021	42.111	0
Inf7 <- Information	0.877	0.876	0.028	30.908	0
Inf8 <- Information	0.912	0.911	0.018	51.563	0
Mark1 <- Market	0.814	0.738	0.276	2.951	0.003
Mark1*Inf1 <- Market*Information	0.699	0.662	0.119	5.893	0
Mark1* Inf3 <-Market*Information	0.658	0.621	0.123	5.326	0
Mark1* Inf7 <-Market*Information	0.694	0.695	0.077	9.035	0
Mark1* Inf8 <-Market*Information	0.706	0.682	0.094	7.547	0
Mark4 <- Market	0.758	0.692	0.249	3.051	0.002
Mark4* Inf1 <-Market*Information	0.633	0.59	0.133	4.767	0
Mark4* Inf3 <-Market*Information	0.607	0.563	0.134	4.521	0
Mark4* Inf7 <-Market*Information	0.626	0.611	0.096	6.555	0
Mark4*Inf8 <- Market*Information	0.646	0.613	0.112	5.791	0
Mark5 <- Market	0.838	0.761	0.266	3.147	0.002
Mark5*Inf1 <- Market*Information	0.69	0.65	0.108	6.392	0
Mark5*Inf3 <- Market*Information	0.655	0.614	0.111	5.899	0
Mark5*Inf7 <- Market*Information	0.676	0.669	0.081	8.357	0
Mark5*Inf8 <- Market*Information	0.695	0.666	0.09	7.71	0
Mark8 <- Market	0.859	0.782	0.239	3.588	0
Mark8*Inf1 <- Market*Information	0.64	0.596	0.141	4.525	0
Mark8*Inf3 <- Market*Information	0.613	0.567	0.141	4.356	0
Mark8*Inf7 <- Market*Information	0.623	0.608	0.122	5.09	0
Mark8*Inf8 <-Market*Information	0.646	0.613	0.128	5.06	0

Table 5-81 shows the T-values and factor loadings of the indicators associated with the structural model of $H_{4\text{-}5}$. It can be observed that the factor loadings of all items belonging to the moderation effect were higher than the threshold limit of 0.7. Furthermore, the obtained T-Statistics of these indicators belonging to the moderation effect (i.e., market * information) were higher than the satisfactory limit ($|\pm 1.96|$). Hence, it can be concluded that these indicators of moderation effect (market * information) interacted significantly between information drivers and DPP.

Table 5-81-Path analysis of hypothesis 4-5. The market variable moderates the information driver and DPP.						
	Path Coefficient (O)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Value	LLCI (2.5%)	ULCI (97.5%)
Information -> DPP	0.887	0.023	37.78	0	0.832	0.923
Market -> DPP	0.089	0.039	2.296	0.022	-0.003	0.152
Market*Information -> DPP	-0.102	0.038	2.682	0.007	-0.19	-0.043

Table 5-82 demonstrates the quality criteria for the sub-hypothesis, including Cronbach's Alpha, CR, and AVE. It can be observed that all criteria were higher than defined threshold limits which approved the reliability and internal consistency of the developed construct for the sub-hypothesis (4-5), and this sub-hypothesis has been certified. Although the R-squared value would not be considered merely to evaluate the model's fitness for the collected data, considering the R-squared value alongside the path coefficient and T-value can produce a reasonable prediction about the hypothesis model. R-squared has been computed and reported for the DPP variable to determine how the fifth sub-hypothesis and its developed construct can estimate the variance. By considering the T-Value (2.682) of the moderator path (market * information → DPP) at a 95% confidence interval and R-squared value (0.827), it can be concluded that the developed construct for the sub-hypothesis (H_{4-5}) was fitted to the collected data and DPP can be explained 82.7% of the variance.

Table 5-82-Quality criteria of hypothesis 4-5 construct. The market variable moderates the information driver and DPP.				
	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)	R-Squared
DPP	0.892	0.925	0.757	0.827
Information	0.92	0.944	0.807	---
Market	0.839	0.89	0.669	---
Market*Information	0.953	0.954	0.568	---

Table 5-83 shows the discriminant validity based on the Fornell-Larcker criterion of sub hypothesis 4-5. As explained in chapter 3 for PLS-SEM path analysis, the square root of AVE would be higher than the correlation coefficient between the variables to satisfy the Fornell-

Larcker criterion. The developed construct based on the definition of the third sub-hypothesis 4-5 has created an acceptable range of discriminant validity.

Table 5-83-Discriminant validity of hypothesis 4-5 construct based on the Fornell-Larcker criterion

	DPP	Information	Market	Market*Information
DPP	0.870			
Information	0.801	0.898		
Market	0.084	0.005	0.818	
Market*Information	-0.23	0.162	0.034	0.754

In conclusion, the quality criteria, discriminant validity, composite reliability, path coefficient, T-statistic, and R-squared values were shown that the research construct of the fifth sub-hypothesis ($H_{4\text{-}5}$) was fitted to the applied data. The market factor moderates the relationship between inventory driver and DPP for the industrial clusters; therefore, the sub hypothesis ($H_{4\text{-}5}$) is supported.

5.12 Analysis of Hypothesis 5

This section requires analysing the relationship between supply chain drivers and DPP with the business's existence as a moderator. The approved business & enterprise variables (as a moderator) were determined in the CFA analysis (see section 5.3), including Bus 1, Bus 2, Bus 3, and Bus 8.

Figure 5-29 (a) and (b) show the path coefficient (O) and T-values of the fifth hypothesis model using two-stage and productivity approaches, respectively, by considering the moderation effect between two variables. However, the productivity approach has given a lower value of path coefficient (O) ($\beta = -0.108, \alpha < 0.05$) and a significant T-value (3.357) in comparison with the two-stage technique ($\beta = -0.092, \alpha < 0.05\ and\ \mathrm{t-value} = 2.224$). Nevertheless, there is no difference between the direction of the path analysis (both approaches were shown adverse effects) and their T-values (higher than 1.960). In this case, the productivity approach generated a low T-statistic value compared to the two stage process, but still, the obtained values for both methods satisfied the criterion. The two stage approach was applied to report the bootstrapping test (T-statistics). While the path analysis is included the outcomes of two-stage and productivity approaches using bootstrapping test to ensure the fifth hypothesis was correctly analysed.

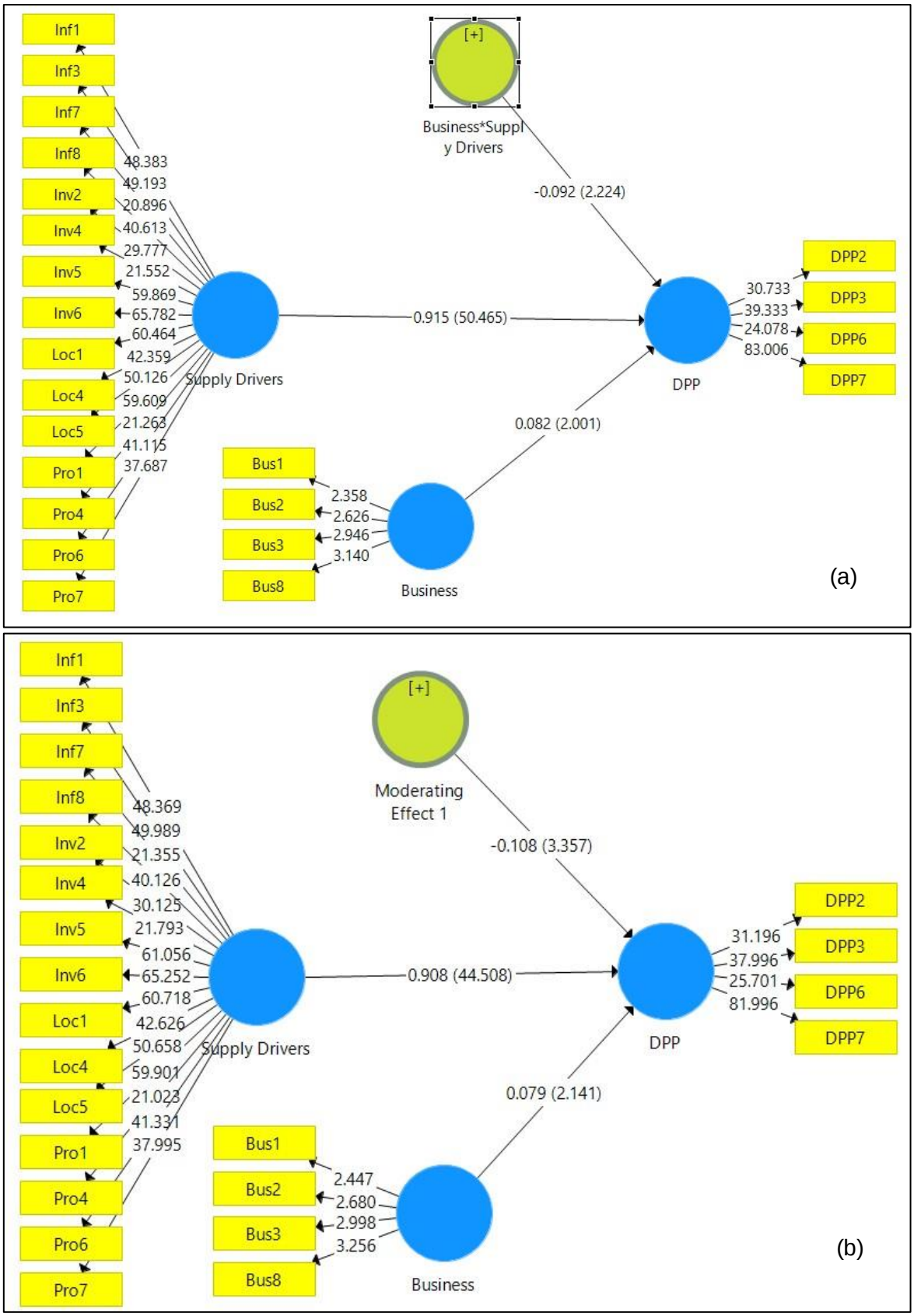


Figure 5-29- (a) shows the structural model of hypothesis 5 using two-stage technique and (b) using productivity approach for the moderation effect. Bootstrapping calculation has been used to determine the path coefficient (t-statistics).

Table 5-84 and Table 5-85 demonstrate outcomes of path analysis using bootstrapping test of the fifth hypothesis through two-stage and productivity approaches, respectively. The path coefficients (-0.092) between the moderation effect (business & enterprise*supply chain drivers) and DPP is negatively moderated by the business & enterprise variable using a two stage approach. Also, the path coefficients (-0.108) between the moderation effect (business & enterprise* supply chain drivers) and DPP is negatively moderated by the business & enterprise variable using the productivity approach. Furthermore, the productivity approach computed a higher value of T-Statistic (3.357) compering with the two-stage method (2.224). However, the T-Statistics of both directions in the presence of business & enterprise moderators were higher than the defined threshold limit. The higher T-Statistic value showed greater evidence against the null hypothesis and a significant difference in standard error units. Also, no zero has been found between LLCI (2.5%) and ULCI (97.5%), which confirmed that the computed T- Statistics were valid at the 95% confidence interval.

Table 5-84-Path analysis of hypothesis 5 **using a two-stage approach**. The moderation effect of business between supply chain drivers and DPP.

	Path Coefficient (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics |O/STDEV|	P Value	LLCI (2.5%)	ULCI (97.5%)
Business -> DPP	0.082	0.079	0.041	2.001	0.045	-0.022	0.146
Business*Supply Drivers -> DPP	-0.092	-0.083	0.041	2.224	0.026	-0.146	0.035
Supply Drivers -> DPP	0.915	0.915	0.018	50.465	0	0.876	0.948

Table 5-85-Path analysis of hypothesis 5 **using the productivity approach**. The moderation effect of business & enterprise between supply chain drivers and DPP

Business -> DPP	0.079	0.071	0.037	2.141	0.032	0.009	0.136
Business*Supply Drivers -> DPP	-0.108	-0.117	0.032	3.357	0.001	-0.184	-0.058
Supply Drivers -> DPP	0.908	0.902	0.02	44.508	0	0.859	0.937

Table 5-86 shows the factor loadings and T-values of indicators for developed construct based on the definition of the fifth hypothesis. The acquired results were computed based on the bootstrapping test when the two-stage approach was applied for the moderator (i.e., business & enterprise) variable. Although it seems this step has been conducted in the CFA section, it is necessary to check the factor loadings and T-values of all approved items by considering the fifth hypothesis and its construct to ensure the reliability of the study has not been compromised. It can be observed that all samples' T-statistics estimate the construct's stability. Furthermore, factor loading of all indicators has had a satisfactory level higher than the threshold limit, proving that the fifth hypothesis was supported based on the result.

Table 5-86-Factor loadings and bootstrapping calculations (T-statistics) of the 5th hypothesis construct. The moderation effect of business between supply chain drivers and DPP.

	Factor Loading (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Value
Bus1 <- Business	0.756	0.666	0.32	2.358	0.018
Bus2 <- Business	0.721	0.635	0.275	2.626	0.009
Bus3 <- Business	0.842	0.744	0.286	2.946	0.003
Bus8 <- Business	0.834	0.731	0.266	3.14	0.002
DPP2 <- DPP	0.859	0.859	0.028	30.733	0
DPP3 <- DPP	0.87	0.872	0.022	39.333	0
DPP6 <- DPP	0.82	0.819	0.034	24.078	0
DPP7 <- DPP	0.927	0.927	0.011	83.006	0
Inf1 <- Supply Drivers	0.903	0.903	0.019	48.383	0
Inf3 <- Supply Drivers	0.901	0.901	0.018	49.193	0
Inf7 <- Supply Drivers	0.809	0.809	0.039	20.896	0
Inf8 <- Supply Drivers	0.884	0.884	0.022	40.613	0
Inv2 <- Supply Drivers	0.85	0.851	0.029	29.777	0
Inv4 <- Supply Drivers	0.807	0.806	0.037	21.552	0
Inv5 <- Supply Drivers	0.927	0.928	0.015	59.869	0
Inv6 <- Supply Drivers	0.931	0.931	0.014	65.782	0
Loc1 <- Supply Drivers	0.93	0.93	0.015	60.464	0
Loc4 <- Supply Drivers	0.896	0.897	0.021	42.359	0
Loc5 <- Supply Drivers	0.909	0.909	0.018	50.126	0

Pro1 <- Supply Drivers	0.923	0.923	0.015	59.609	0
Pro4 <- Supply Drivers	0.816	0.816	0.038	21.263	0
Pro6 <- Supply Drivers	0.891	0.891	0.022	41.115	0
Pro7 <- Supply Drivers	0.897	0.897	0.024	37.687	0
Supply Drivers * Business <- Business*Supply Drivers	0.931	0.949	0.09	10.292	0

Table 5-87 shows the quality criteria for the fifth hypothesis, including Cronbach's Alpha, CR, and AVE. It can be observed that all criteria were higher than defined threshold limits which approved the reliability and internal consistency of the developed construct for the fifth hypothesis.

Although the R-squared value would not be considered merely to evaluate the model's fitness for the collected data, considering the R-squared value alongside the path coefficient and T-value can produce a reasonable prediction about the hypothesis model. R-squared has been computed and reported for the DPP variable to determine how the fifth hypothesis and its developed construct can strongly estimate the variance. By considering the T-Value (3.357) of the moderator path (business & enterprise * supply chain driver → DPP) at a 95% confidence interval and R-squared value (0.868), it can be concluded that the developed construct for the fifth hypothesis was fitted to the collected data and DPP can be explained 86.8% of the variance.

Table 5-87-Quality criteria of hypothesis 5, using productivity approach. The moderation effect of business & enterprise variable between supply chain drivers and DPP.

	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)	R-squared
Business	0.809	0.869	0.625	---
DPP	0.892	0.925	0.757	0.868
Business*Supply drivers	0.984	0.984	0.515	---
Supply Drivers	0.98	0.982	0.785	----

Table 5-88 shows the discriminant validity based on the Fornell-Larcker criterion of hypothesis 5. As explained in chapter 3, for PLS-SEM path analysis, the square root of AVE would be higher than the correlation coefficient between the variables to satisfy the Fornell-Larcker criterion. The developed construct based on the definition of the fifth hypothesis has created an acceptable range of discriminant validity.

Table 5-88-Discriminant validity of the structural model of 5th hypothesis using productivity approach based on the Fornell-Larcker criterion.				
	Business	DPP	Business*Supply drivers	Supply Drivers
Business	0.790			
DPP	0.082	0.870		
Business*Supply drivers	0.059	0.24	0.718	
Supply Drivers	0.09	0.824	0.164	0.886

In conclusion, the quality criteria, discriminant validity, composite reliability, path coefficient, T-statistic, and R-squared values were shown that the research construct of the fifth hypothesis (H_5) was fitted to the applied data. The relationship between supply chain drivers and DPP is moderated by the market factor of the industrial clusters, and therefore the fifth hypothesis (H_5) is supported. However, suppose the interaction effect (i.e., business & enterprise * supply chain drivers) exists between two variables in the presence of the moderator. In that case, it is required to complete the conducted analysis by drawing the interaction plots and applying SSA between the variables to grasp the direction of the moderation effect.

5.13 Simple slop analysis of H5

Table 5-89 shows the steps of two-way linear interaction effects (Dawson 2014) to plot the moderation effect of the fifth hypothesis via regression analysis. The values have been collected from the outcome of bootstrapping test using SmartPLS software (V 3).

Figure 5-29 shows the disordinal interaction effect of a moderator (i.e., Business & Enterprise * supply chain drivers) on the position of DPP. The X-axis represents the independent variable (SC drivers), and Y-axis represents a dependent variable (DPP).

The green line shows the effect of business & enterprise moderation with a higher standard deviation (adding one SD unit to the mean value of the moderator), and the red line shows the effect of business & enterprise moderation with a lower standard deviation (subtracting one SD unit from the mean value of moderator). Also, the blue line shows the avenge effect of business & enterprise between supply chain drivers and DPP. As discussed, the disordinal

interaction occurs when high, average, and low values of the moderator's mean cross over each other in the defined borderlines of IV and DV (Dawson and Richter 2006).

In this study, the moderator's higher effect (level) can be interpreted as a substantial effect on business & enterprise based on the validated measures from CFA. The lower moderation effect can be labelled as a weak effect on business & enterprise as a moderator. The higher and lower moderation effects indicated how the business & enterprise could interact between the IV and DV in the industrial clusters. The difference between the higher and lower effects of business & enterprise depends on the value of SC drivers.

The slopes of the green line indicated that the higher effect of the moderator increased the DPP value from -0.72 to 0.87 with the gradient of 0.785, while the lower effect of business & enterprise increased the value of DPP from -1.1 to 0.93 with the slope of 1.005. Hence, by considering the gradients between two lines, the lower effect of the moderator (red line) has a more significant influence on the negative values of the DPP compared to the higher effect of the moderator. Moreover, the cross-over point (0.76, 0.68) occurred at the top-right corner of the graph, which shows the moderator (i.e., business & enterprise) has interacted between IV and DV at the higher positive values rather than negative values of the DPP.

Furthermore, before the interaction effect (cross-over point), the position of the higher impact of the business & enterprise (i.e., green line) was more significant than the lower effect of the moderator (i.e., red line). After the interaction point, the lower effect of the moderator (i.e., red line) was higher than the higher effect. Indeed, the interaction effect inverted the moderation effect from a higher (green line) to a lower (red line) effect after the cross-over point. Hence, this phenomenon shows that the lower effect of the moderator (red line) has a more significant impact on the DPP values than the higher effect of business & enterprise (green line) after the cross-over point. In other words, the moderator has a minor negative impact on the SC drivers and DPP after the interaction point where these variables have reached higher values. This fact was matched with the results of the negative path coefficient of the moderation effect (i.e., factor loading of business & enterprise * Supply drivers is -0.109).

Moreover, on the down-left corner of the graph (where the SC drivers and DPP have a negative value), there is a more significant variance between the higher and lower effect of the moderators' lines (i.e., a vertical gap between red and green lines). There was a small vertical gap between the red and green lines after the cross-over point (orange point in the graph), where the DPP has a maximum positive value. The variance between the higher and lower effects was insignificant after the interaction effect.

In conclusion, the simple slope analysis demonstrated that the interaction effect between moderator and DPP (i.e., business & enterprise * Supply drivers → DPP) has occurred within the defined standard deviations; however, the interaction effect between DPP and SC drivers was insignificant.

Table 5-89-The worksheet plots of two-way linear interaction effects via regression analysis (PLS and bootstrapping tests) to conduct simple slope analysis (adapted from (Dawson 2014).

Path Coefficients	**Values**
Independent variable (Supply Chain Drivers)	0.908
Moderator (Business)	0.079
Interaction (Supply chain Drivers* Business & Enterprise)	-0.108
Dependent variable	DPP
Intercept / Constant	0
Means / SDs of variables:	**Values**
Mean of the independent variable	0.902
SD of the independent variable	0.020
Mean of moderator	0.071
SD of moderator	0.037

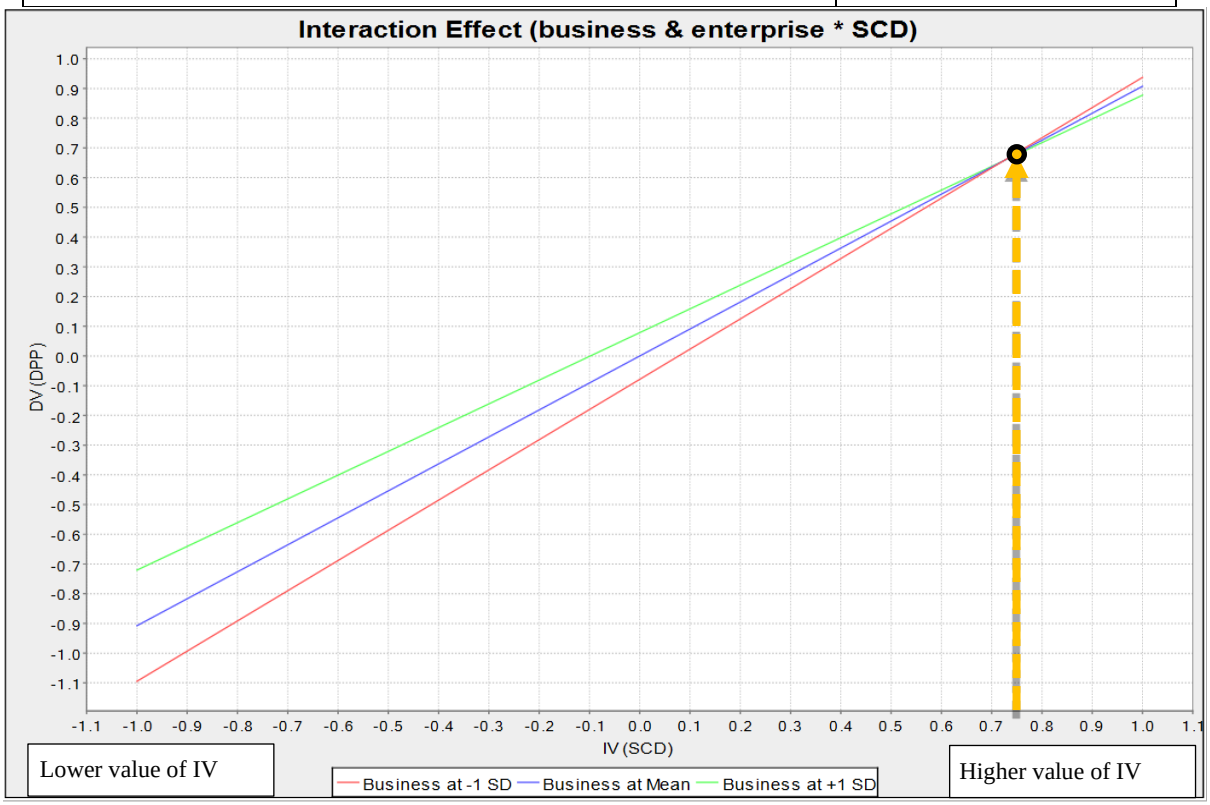


Figure 5-30- Shows the simple slope analysis of the interaction effect (business & enterprise * supply chain drivers) on the position of DPP related to fifth hypothesis.

5.13.1 Hypothesis 5-1: The relationship between production driver and DPP is moderated by the business & enterprise

This section requires analysing the relationship between production and DPP with the existence of the business & enterprise factor as a moderator. The indicators of the business & enterprise (as a moderator variable) were determined in the CFA, including Bus 1, Bus 2, Bus 3, and Bus 8. Also, within the CFA, the production indicators were listed as Pro 1, Pro 4, Pro 6, and Pro 7. Figure 5-31 shows the path coefficients (O) and T-values of the sub-hypothesis model 3-1 using the productivity approach by considering the moderation effect between two variables (i.e., Production → DPP). The path coefficient (O) of the moderation effect (i.e., business & enterprise * Production) was computed ($\beta = -0.109$ @ $\alpha < 0.05$) and the T-value was (1.882). The obtained T-value was insignificant (lower than 1.96) using the bootstrapping test. The obtained path coefficient of the moderation effect is negative, which shows a reverse correlation between the moderation effect and DPP. Furthermore, the bootstrapping analysis also showed that the path analysis based on the definition of sub hypothesis (5-1) was accepted between business & enterprise and DPP (business & enterprise →DPP), where the path coefficient was ($\beta = 0.277$@ $\alpha < 0.05$) and the T-value (2.108). Although the obtained t-value (2.108) of the path analysis was significant (higher than 1.96) using the bootstrapping test, it is necessary to conduct further analysis to investigate whether the indicators of moderation effect were accepted.

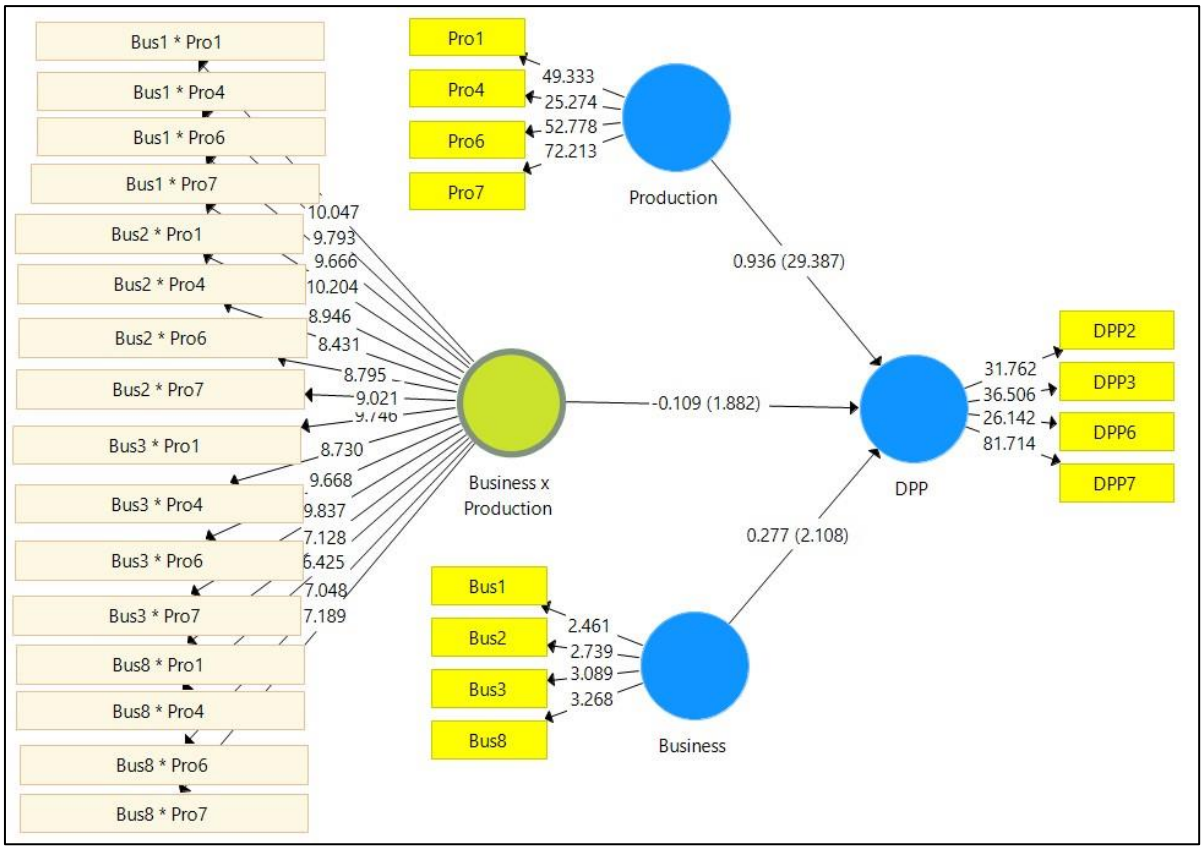


Figure 5-31- The structural model of sub-hypothesis 5-1. Bootstrapping analysis shows the path coefficient and (T-statistics) of the moderation effect (i.e., business & enterprise * production) between production driver and DPP.

Table 5-90 shows the T-values and factor loadings of the indicators associated with the structural model of $H_{5\text{-}1}$. It can be observed that the factor loadings of all the indicators belonging to the moderation effect (business & enterprise * Production) were higher than the threshold limit of 0.7. Furthermore, the obtained T-Statistics of the indicators belonging to the moderation effect (i.e., Business & enterprise * production) were higher than the satisfactory limit (|±1.96|). It could be that the indicators of moderation effect (Business & enterprise * production) did not interact between the production driver and DPP. However, further path analysis must approve the factor loadings and T-test results.

Table 5-90-Bootstrapping calculation (T-statistics) of hypothesis 5-1. The business variable moderates the production driver and DPP.

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values

Bus1 <- Business	0.76	0.671	0.309	2.461	0.014
Bus1 * Pro1 <-Business*Production	1.637	1.603	0.163	10.047	0
Bus1 * Pro4 <-Business*Production	1.542	1.495	0.157	9.793	0
Bus1 * Pro6 <-Business*Production	1.631	1.6	0.169	9.666	0
Bus1 * Pro7 <-Business*Production	1.648	1.612	0.162	10.204	0
Bus2 <- Business	0.72	0.64	0.263	2.739	0.006
Bus2 * Pro1 <-Business*Production	1.642	1.629	0.184	8.946	0
Bus2 * Pro4 <-Business*Production	1.592	1.571	0.189	8.431	0
Bus2 * Pro6 <-Business*Production	1.626	1.615	0.185	8.795	0
Bus2 * Pro7 <-Business*Production	1.654	1.641	0.183	9.021	0
Bus3 <- Business	0.844	0.749	0.273	3.089	0.002
Bus3 * Pro1 <-Business*Production	1.799	1.785	0.185	9.746	0
Bus3 * Pro4 <-Business*Production	1.722	1.692	0.197	8.73	0
Bus3 * Pro6 <-Business*Production	1.79	1.78	0.185	9.668	0
Bus3 * Pro7 <-Business*Production	1.81	1.794	0.184	9.837	0
Bus8 <- Business	0.832	0.734	0.255	3.268	0.001
Bus8 * Pro1 <-Business*Production	1.586	1.584	0.223	7.128	0
Bus8 * Pro4 <-Business*Production	1.532	1.517	0.238	6.425	0
Bus8 * Pro6 <-Business*Production	1.572	1.573	0.223	7.048	0
Bus8 * Pro7 <-Business*Production	1.599	1.596	0.222	7.189	0
DPP2 <- DPP	0.86	0.86	0.027	31.762	0
DPP3 <- DPP	0.865	0.866	0.024	36.506	0
DPP6 <- DPP	0.826	0.823	0.032	26.142	0
DPP7 <- DPP	0.925	0.926	0.011	81.714	0
Pro1 <- Production	0.907	0.907	0.018	49.333	0
Pro4 <- Production	0.849	0.847	0.034	25.274	0
Pro6 <- Production	0.915	0.916	0.017	52.778	0
Pro7 <- Production	0.934	0.934	0.013	72.213	0

Table 5-91 demonstrates the path coefficient and T-Statistic of the pathway between three variables: production, DPP, and basis & foundation. The moderation effect has been defined as a production * business & enterprise, which is the central part of the structural model based on the definition of sub-hypothesis (5-1). The T-Statistic value between moderator and DPP

(2.108 @ P-value > 0.05) was significant; however, the T-value of the moderation effect (1.882@ P-value < 0.05) was lower than|±1.96|. Also, there is a zero between LLCI and ULCI, which is violated the T-statistic of moderation effect. It can be concluded that all pathways of developed construct based on the definition of sub-hypothesis 5-1 were not approved, and therefore the sub-hypothesis 5-1 was rejected. However, the quality criteria of sub-hypothesis 5-1 were studied to determine whether the rejection process of the H_{5-1} was correct.

Table 5-91-Path analysis of hypothesis 5-1. The business & enterprise variable moderates the production driver and DPP.

	Path Coefficient (O)	Standard Deviation (STDEV)	T Statistics |O/STDEV|	P Value	LLCI (2.5%)	ULCI (97.5%)
Business -> DPP	0.277	0.131	2.108	0.035	0.277	0.131
Business* Production -> DPP	-0.109	0.058	1.882	0.06	-0.109	0.058
Production -> DPP	0.936	0.032	29.387	0	0.936	0.032

Table 5-92 demonstrates the quality criteria, including Cronbach's Alpha, CR, and AVE for the sub-hypothesis 5-1. It can be observed that the AVE criterion for the moderation effect (Business & enterprise * production) was very low in comparison to the other values. However still higher than the threshold limit (0.5), which indicated the variable's convergent validity.

Due to the unsatisfactory values of T-Statistic, LLCI & ULCI, and path coefficient for the moderation effect (business & enterprise * production), the sub-hypothesis 5-1 was not supported. Therefore, it is unnecessary to investigate the discriminant validity of hypothesis 5-1 based on the Fornell-Larcker criterion.

Table 5-92-Quality criteria of hypothesis 5-1 construct. The business variable moderates the production driver and DPP.

	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)	R-squared
Business	0.809	0.869	0.625	---

Business*Production	0.952	0.956	0.577	---
DPP	0.892	0.925	0.757	0.813
Production	0.923	0.946	0.814	----

In conclusion, the AVE, path coefficient, T-Statistic, and factor loadings values showed that the sub-hypothesis's research construct (H_{5-1}) was not fitted to the applied data. The relation between production driver and DPP has not been moderated by the business & enterprise; therefore, the sub-hypothesis (H_{5-1}) is not supported.

5.13.2 Hypothesis 5-2: The relationship between location driver and DPP is moderated by the business & enterprise

In this section, the relationship between location and DPP with the existence of the Business & enterprise as a moderator was analysed. The indicators of the business & enterprise (as a moderator variable) were reported in the previous section after conducting CFA, including Bus 1, Bus 2, Bus 3, and Bus 8. Also, within the CFA, the location indicators were listed as Loc1, Loc4, and Loc 5. Figure 5-32 shows the path coefficients (O) and T-values of the developed construct based on the definition of the sub-hypothesis 5-2 using the productivity approach by considering the moderation effect between two variables (Location → DPP). The path coefficient (O) of the moderation effect (i.e., business & enterprise * Location → DPP) was computed ($\beta = -0.154$ @ $\alpha < 0.05$) and the T-value was (3.461). The obtained path coefficient of the moderation effect is negative, which shows that there was a reverse correlation between the moderation effect and DPP. Furthermore, the bootstrapping analysis also showed that the path analysis based on the definition of sub-hypothesis (5-2) was rejected between business & enterprise and DPP, where the path coefficient was ($\beta = 0.071$ @ $\alpha < 0.05$) and the T-value (1.848). Although the obtained t-value (4.564) of the path analysis was significant (higher than 1.96) using the bootstrapping test, it is necessary to conduct further analysis to investigate whether the indicators of moderation effect were accepted.

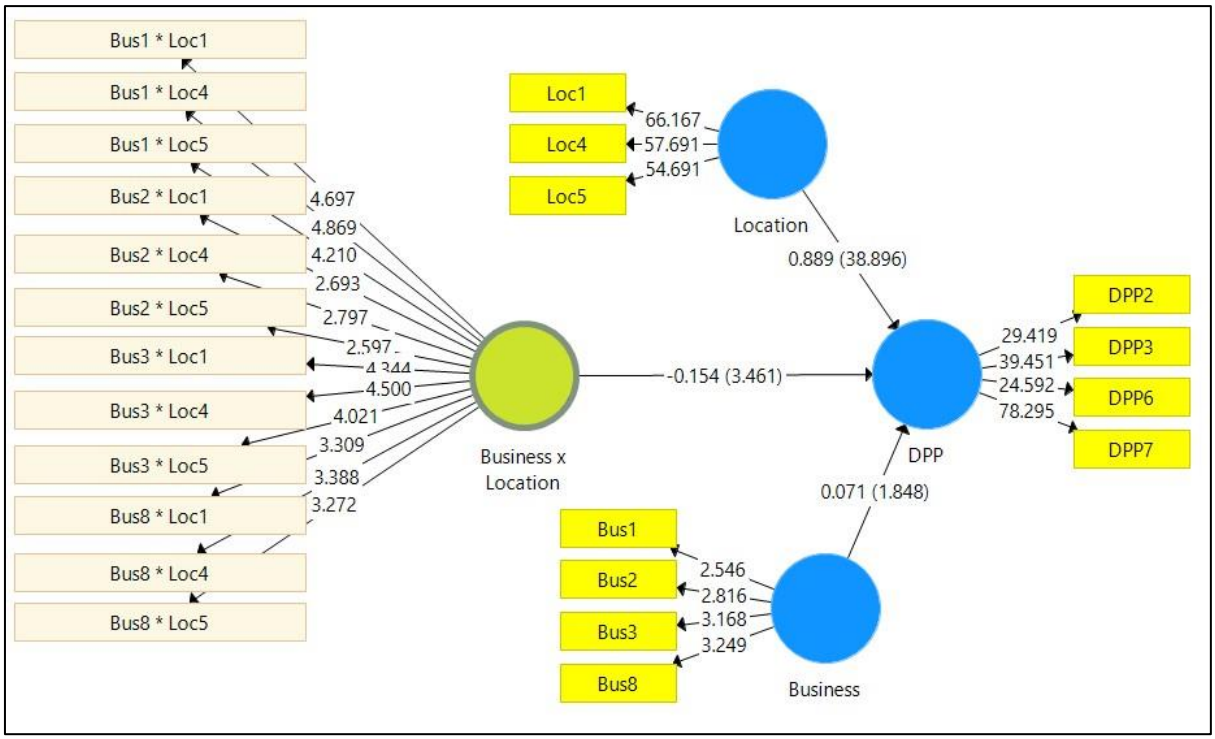


Figure 5-32- The structural model of hypothesis 5-2. Bootstrapping analysis shows the path coefficient (T-statistics) of the moderation effect (i.e., business & enterprise) between location driver and DPP.

Table 5-93 shows the T-values and factor loadings of the indicators associated with the structural model of H_{5-2}. It can be observed that these indicators of moderation effect (business & enterprise * location) interacted between location drivers and DPP significantly. However, the path analysis and the selected quality criteria must be satisfied to complete this analysis.

Table 5-93-Bootstrapping calculation (T-statistics) of hypotheses 4-2. The business variable moderates the location driver and DPP.

	Factor Loading (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Bus1 <- Business	0.76	0.675	0.298	2.546	0.011
Bus1 * Loc1 <- Business x Location	0.772	0.729	0.164	4.697	0
Bus1 * Loc4 <- Business x Location	0.773	0.734	0.159	4.869	0
Bus1 * Loc5 <- Business x Location	0.75	0.698	0.178	4.21	0
Bus2 <- Business	0.72	0.645	0.256	2.816	0.005
Bus2 * Loc1 <- Business x Location	0.585	0.529	0.217	2.693	0.007
Bus2 * Loc4 <- Business x Location	0.592	0.538	0.212	2.797	0.005
Bus2 * Loc5 <- Business x Location	0.581	0.516	0.224	2.597	0.009

Bus3 <- Business	0.844	0.754	0.266	3.168	0.002
Bus3 * Loc1 <- Business x Location	0.774	0.713	0.178	4.344	0
Bus3 * Loc4 <- Business x Location	0.778	0.72	0.173	4.5	0
Bus3 * Loc5 <- Business x Location	0.762	0.692	0.19	4.021	0
Bus8 <- Business	0.832	0.737	0.256	3.249	0.001
Bus8 * Loc1 <- Business x Location	0.661	0.618	0.2	3.309	0.001
Bus8 * Loc4 <- Business x Location	0.667	0.625	0.197	3.388	0.001
Bus8 * Loc5 <- Business x Location	0.657	0.604	0.201	3.272	0.001
DPP2 <- DPP	0.856	0.855	0.029	29.419	0
DPP3 <- DPP	0.87	0.87	0.022	39.451	0
DPP6 <- DPP	0.824	0.823	0.033	24.592	0
DPP7 <- DPP	0.926	0.926	0.012	78.295	0
Loc1 <- Location	0.937	0.937	0.014	66.167	0
Loc4 <- Location	0.927	0.927	0.016	57.691	0
Loc5 <- Location	0.938	0.938	0.017	54.691	0

Table 5-94 shows the path coefficient and T-Statistic of the pathway between three variables: location, DPP, and basis & foundation. The moderation effect has been defined as a location * business & enterprise, which is the main part of the structural model based on the definition of sub-hypothesis (5-2). The T-Statistic value between moderator and DPP (1.629 @ P-value > 0.05) was insignificant, however the T-value of the moderation effect (4.186 @ P-value < 0.05) was higher than$|\pm 1.96|$. It can be concluded that the main pathways of the developed construct based on the definition of sub-hypothesis 5-2 were not approved, and therefore the $H_{5\text{-}2}$ was rejected. However, the quality criteria of sub-hypothesis 5-2 were studied to determine whether the rejection process of the $H_{5\text{-}2}$ was validated.

Table 5-94-Path analysis of hypothesis 5-2. The business variable moderates the location driver and DPP.

	Path Coefficient (O)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Value	LLCI (2.5%)	ULCI (97.5%)
Business -> DPP	0.071	0.039	1.848	0.065	-0.02	0.135
Business*Location -> DPP	-0.154	0.044	3.461	0.001	-0.245	-0.065
Location -> DPP	0.889	0.023	38.896	0	0.836	0.925

Table 5-95 shows the quality criteria, including Cronbach's Alpha, CR, and AVE for the sub hypothesis 5-2. It can be observed that the quality criteria of the construct have been approved. However, due to the unsatisfactory values of the T-Statistic and path coefficient for the moderator (business & enterprise), the sub-hypothesis 5-2 was not accepted. Therefore, it is unnecessary to investigate the discriminant validity of hypothesis 5-2 based on the Fornell-Larcker criterion.

Table 5-95-Quality criteria of hypothesis 5-2 construct. The location driver and DPP is moderated by the business variable.

	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)	R-squared
Business	0.809	0.869	0.625	---
Business*Location	0.946	0.952	0.628	---
DPP	0.892	0.925	0.756	0.834
Location	0.927	0.954	0.873	---

In conclusion, the AVE, path coefficient, T-Statistic, and factor loadings values showed that the sub-hypothesis's research construct (H_{5-2}) was not fitted to the applied data. The relation between location driver and DPP has not been moderated by the business & enterprise; therefore, the sub-hypothesis (H_{5-2}) was not supported.

5.13.3 Hypothesis 5-3: The relationship between inventory driver and DPP is moderated by the business & enterprise

In this section, the relationship between inventory and DPP with the existence of the Basis & Foundation as a moderator was analysed. The indicators of the business & enterprise (as a moderator variable) were reported in the previous section after conducting CFA, including Bus 1, Bus 2, Bus 3, and Bus 8. Also, within the CFA, the inventory indicators were listed as Inv2, Inv4, Inv5 and Inv6. Figure 5-33 shows the path coefficients (O) and T-values of the developed construct based on the definition of the sub-hypothesis 5-3 using the productivity approach by considering the moderation effect (business & enterprise * inventory) between two variables (inventory → DPP). The path coefficient (O) of the moderation effect (i.e., business & enterprise * inventory →DPP) was computed ($\beta = -0.115$ @ $\alpha < 0.05$) and the T-value was (3.475). The obtained path coefficient of the moderation effect is negative, which

shows that there was a reverse correlation between the moderation effect and DPP. Moreover, the bootstrapping analysis also showed that the path analysis based on the definition of sub hypothesis (5-3) was accepted between business & enterprise and DPP, where the path coefficient was ($\beta = 0.085$ @ $\alpha < 0.05$) and the T-value (2.322). Although the obtained T-values of the path analysis were significant (higher than 1.96) using the bootstrapping test, it is necessary to conduct further analyses to investigate whether the interaction of indicators belonging to the moderation effect was validated.

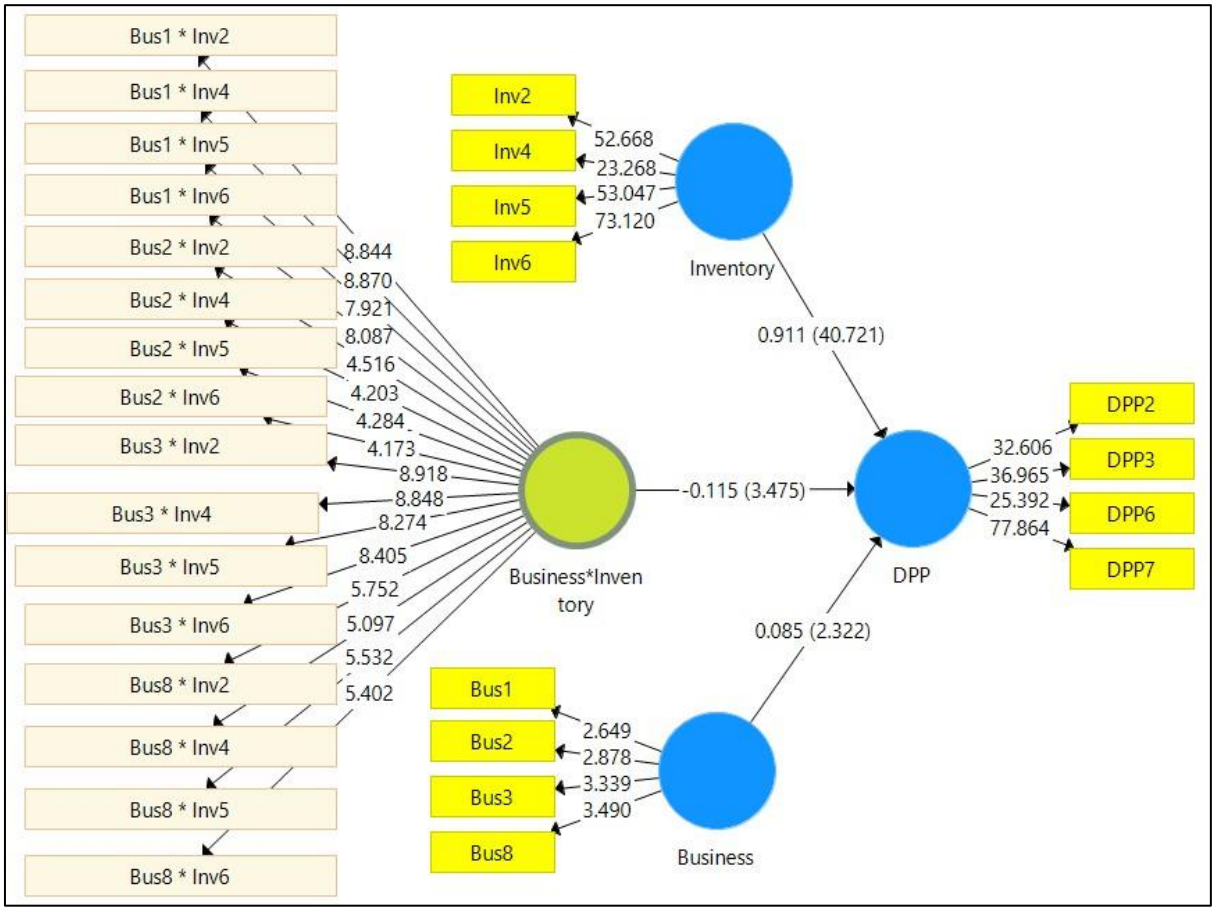


Figure 5-33- The structural model of sub-hypothesis 5-3. Bootstrapping analysis shows the path coefficient and (T-statistics) of the moderation effect (i.e., business & enterprise) between inventory driver and DPP.

Table 5-96 shows the T-values and factor loadings of the indicators associated with the structural model of $H_{5\text{-}3}$. It can be observed that the factor loadings of all items belonging to the moderation effect were higher than the threshold limit of 0.7. Furthermore, the obtained T-Statistics of these indicators belonging to the moderation effect (i.e., business & enterprise * inventory) were higher than the satisfactory limit ($|\pm 1.96|$). Hence, it can be concluded that

these indicators of moderation effect (business & enterprise * inventory) interacted significantly between inventory drivers and DPP.

Table 5-96- Bootstrapping calculation (T-statistics) of hypothesis 5-3. The business variable moderates the inventory driver and DPP.

	Factor Loading (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Bus1 <- Business	0.759	0.678	0.287	2.649	0.008
Bus1 * Inv2 <- Business*Inventory	0.658	0.641	0.074	8.844	0
Bus1 * Inv4 <- Business*Inventory	0.617	0.626	0.07	8.87	0
Bus1 * Inv5 <- Business*Inventory	0.667	0.646	0.084	7.921	0
Bus1 * Inv6 <- Business*Inventory	0.675	0.655	0.083	8.087	0
Bus2 <- Business	0.72	0.648	0.25	2.878	0.004
Bus2 * Inv2 <- Business*Inventory	0.551	0.52	0.122	4.516	0
Bus2 * Inv4 <- Business*Inventory	0.497	0.485	0.118	4.203	0
Bus2 * Inv5 <- Business*Inventory	0.55	0.515	0.128	4.284	0
Bus2 * Inv6 <- Business*Inventory	0.549	0.517	0.132	4.173	0
Bus3 <- Business	0.844	0.757	0.253	3.339	0.001
Bus3 * Inv2 <- Business*Inventory	0.717	0.682	0.08	8.918	0
Bus3 * Inv4 <- Business*Inventory	0.674	0.66	0.076	8.848	0
Bus3 * Inv5 <- Business*Inventory	0.723	0.684	0.087	8.274	0
Bus3 * Inv6 <- Business*Inventory	0.727	0.69	0.086	8.405	0
Bus8 <- Business	0.833	0.745	0.239	3.49	0
Bus8 * Inv2 <- Business*Inventory	0.608	0.579	0.106	5.752	0
Bus8 * Inv4 <- Business*Inventory	0.554	0.546	0.109	5.097	0
Bus8 * Inv5 <- Business*Inventory	0.611	0.58	0.11	5.532	0
Bus8 * Inv6 <- Business*Inventory	0.609	0.58	0.113	5.402	0
DPP2 <- DPP	0.862	0.862	0.026	32.606	0
DPP3 <- DPP	0.866	0.865	0.023	36.965	0
DPP6 <- DPP	0.824	0.823	0.032	25.392	0
DPP7 <- DPP	0.924	0.923	0.012	77.864	0
Inv2 <- Inventory	0.907	0.907	0.017	52.668	0
Inv4 <- Inventory	0.824	0.823	0.035	23.268	0
Inv5 <- Inventory	0.92	0.92	0.017	53.047	0
Inv6 <- Inventory	0.934	0.934	0.013	73.12	0

Table 5-97 shows the path coefficient and T-Statistic between two main variables (i.e., inventory driver & DPP), moderator (i.e., business & enterprise) and DPP, and moderation effect (i.e., business & enterprise * inventory) and DDP at a 95% of confidence level. Both path coefficient (-0.115) and T-value (3.475) of the moderation effect were higher than threshold limits, and there is no zero between the lower and higher limit of confidence intervals. Hence, it can be concluded that the T-statistic of the moderation path of the moderation effect (business & enterprise * inventory →DPP) estimates the stability of the construct at the defined confidence interval. Thereby, it can be stated that the sub-hypothesis (H_{5-3}) has been approved statistically. However, the quality criteria of the developed construct have been checked to ensure the reliability and internal consistency of the construct have not been neglected.

Table 5-97-Path analysis of hypothesis 5-3. The business & enterprise variable moderates the inventory driver and DPP.

	Path Coefficient (O)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Value	LLCI (2.5%)	ULCI (97.5%)
Business -> DPP	0.085	0.036	2.322	0.02	-0.003	0.142
Business*Inventory -> DPP	-0.115	0.033	3.475	0.001	-0.194	-0.065
Inventory -> DPP	0.911	0.022	40.721	0	0.856	0.944

Table 5-98 demonstrates the quality criteria for the sub-hypothesis, including Cronbach's Alpha, CR, and AVE. It can be observed that all criteria were higher than defined threshold limits which approved the reliability and internal consistency of the developed construct for the sub-hypothesis (5-3), and this sub-hypothesis has been certified. Although the R-squared value would not be considered merely to evaluate the model's fitness in collected data, considering the R-squared value alongside the path coefficient and T-value can produce a reasonable prediction about the hypothesis model. R-squared has been computed and reported for the DPP variable to determine how the third sub-hypothesis and its developed construct can strongly estimate the variance. By considering the T-Value (3.475) of the moderator path (business & enterprise * inventory → DPP) at a 95% confidence interval and R-squared value (0.902), it can be concluded that the developed construct for the sub-hypothesis (H_{5-3}) was fitted to the collected data and DPP can be explained 90.2% of the variance.

Table 5-98-Quality criteria of hypothesis 5-3 construct. The business & enterprise variable moderates the location driver and DPP.				
	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)	R-Squared
Business	0.809	0.869	0.625	---
Business*Inventory	0.938	0.943	0.511	---
DPP	0.892	0.925	0.757	0.879
Inventory	0.918	0.943	0.805	---

Table 5-99 shows the discriminant validity based on the Fornell-Larcker criterion of sub hypothesis 5-3. As explained in chapter 3 for PLS-SEM path analysis, the square root of AVE would be higher than the correlation coefficient between the variables to satisfy the Fornell-Larcker criterion. The developed construct based on the definition of the sub-hypothesis 5-3 has created an acceptable range of discriminant validity.

Table 5-99-Discriminant validity of hypothesis 5-3 construct based on the Fornell-Larcker criterion.				
	Business	Business*Inventory	DPP	Inventory
Business	0.791			
Business*Inventory	0.035	0.715		
DPP	0.083	-0.261	0.87	
Inventory	0.002	-0.179	0.829	0.897

In conclusion, the quality criteria, discriminant validity, composite reliability, path coefficient, T-statistic, and R-squared values showed that the third sub-hypothesis (H5-3) research construct was fitted to the applied data. The business & enterprise factor moderates the relationship between inventory driver and DPP for the industrial clusters, and therefore the sub-hypothesis ($H_{5\text{-}3}$) was supported.

5.13.4 Hypothesis 5-5: The relation between information driver and DPP is moderated by the business & enterprise

In this section, the relationship between information and DPP with the existence of the Basis & Foundation as a moderator was analysed. The indicators of the business & enterprise (as a

moderator variable) were reported in the previous section after conducting CFA, including Bus1, Bus 2, Bus 3, and Bus 8. Also, within the CFA, the information indicators were listed as Inf1, Inf3, Inf7, and Inf8.

Figure 5-34 shows the path coefficients (O) and T-values of the developed construct based on the definition of the sub-hypothesis 5-5 using the productivity approach by considering the moderation effect (business & enterprise * information) between two variables (information → DPP). The path coefficient (O) of the moderation effect (i.e., business & enterprise * information →DPP) was computed ($\beta = -0.115$ @ $\alpha < 0.05$) and the T-value was (2.846). The obtained path coefficient of the moderation effect is negative, which shows that there was a reverse correlation between the moderation effect and DPP. Moreover, the bootstrapping analysis also showed that the path analysis based on the definition of sub-hypothesis (5-5) was accepted between business & enterprise and DPP, where the path coefficient was ($\beta = 0.093$ @ $\alpha < 0.05$) and the T-value (2.262). Although the obtained T-values of the path analysis were significant (higher than 1.96) using the bootstrapping test, it is necessary to conduct further analyses to investigate whether the interaction of indicators belonging to the moderation effect was validated.

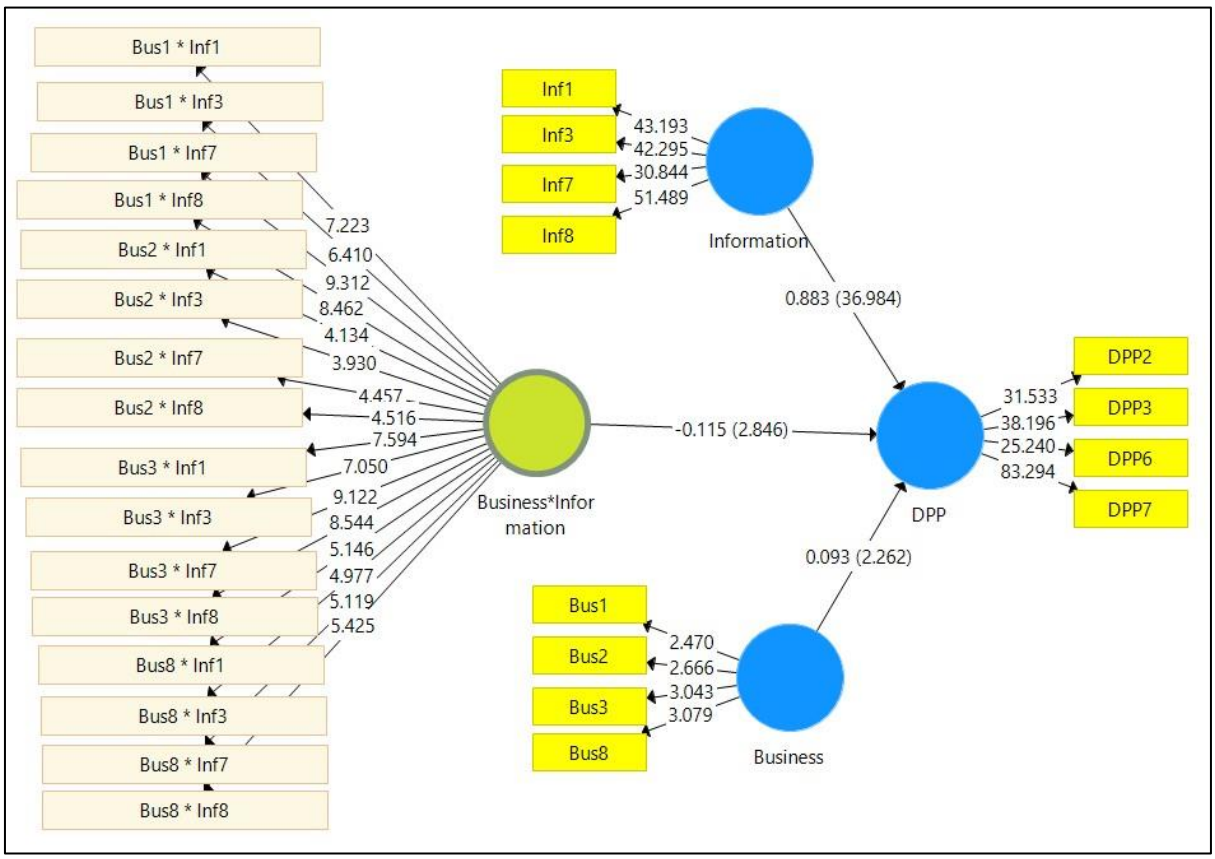


Figure 5-34- The structural model of hypothesis 5-5. Bootstrapping analysis shows the path coefficient (T-statistics) of the moderation effect (i.e., business & enterprise * information) between information driver and DPP.

Table 5-100 shows the T-values and factor loadings of the indicators associated with the structural model of $H_{5\text{-}5}$. It can be observed that the factor loadings of all items belonging to the moderation effect were higher than the threshold limit of 0.7. Furthermore, the obtained T-Statistics of these indicators belonging to the moderation effect (i.e., business & enterprise * information) were higher than the satisfactory limit ($|\pm 1.96|$). Hence, it can be concluded that the indicators of moderation effect (business & enterprise * information) interacted significantly between information drivers and DPP.

Table 5-100-Bootstrapping calculation (T-statistics) of hypothesis 5-5. The business variable moderates the information driver and DPP.

	Factor Loading (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Bus1 <- Business	0.757	0.671	0.306	2.47	0.014
Bus1 * Inf1 <-Business*Information	0.676	0.652	0.094	7.223	0
Bus1 * Inf3 <-Business*Information	0.629	0.604	0.098	6.41	0
Bus1 * Inf7 <-Business*Information	0.654	0.661	0.07	9.312	0
Bus1 * Inf8 <-Business*Information	0.674	0.659	0.08	8.462	0
Bus2 <- Business	0.721	0.642	0.27	2.666	0.008
Bus2 * Inf1 <-Business*Information	0.551	0.514	0.133	4.134	0
Bus2 * Inf3 <-Business*Information	0.522	0.484	0.133	3.93	0
Bus2 * Inf7 <-Business*Information	0.529	0.515	0.119	4.457	0
Bus2 * Inf8 <-Business*Information	0.558	0.529	0.124	4.516	0
Bus3 <- Business	0.843	0.746	0.277	3.043	0.002
Bus3 * Inf1 <-Business*Information	0.722	0.682	0.095	7.594	0
Bus3 * Inf3 <-Business*Information	0.685	0.643	0.097	7.05	0
Bus3 * Inf7 <-Business*Information	0.699	0.685	0.077	9.122	0
Bus3 * Inf8 <-Business*Information	0.721	0.689	0.084	8.544	0
Bus8 <- Business	0.834	0.725	0.271	3.079	0.002
Bus8 * Inf1 <-Business*Information	0.614	0.584	0.119	5.146	0
Bus8 * Inf3 <-Business*Information	0.582	0.55	0.117	4.977	0

Bus8 * Inf7 <-Business*Information	0.582	0.575	0.114	5.119	0
Bus8 * Inf8 <-Business*Information	0.611	0.588	0.113	5.425	0
DPP2 <- DPP	0.861	0.861	0.027	31.533	0
DPP3 <- DPP	0.868	0.868	0.023	38.196	0
DPP6 <- DPP	0.821	0.821	0.033	25.24	0
DPP7 <- DPP	0.926	0.926	0.011	83.294	0
Inf1 <- Information	0.909	0.908	0.021	43.193	0
Inf3 <- Information	0.895	0.895	0.021	42.295	0
Inf7 <- Information	0.877	0.877	0.028	30.844	0
Inf8 <- Information	0.912	0.911	0.018	51.489	0
Bus1 <- Business	0.757	0.671	0.306	2.47	0.014
Bus1 * Inf1 <-Business*Information	0.676	0.652	0.094	7.223	0
Bus1 * Inf3 <-Business*Information	0.629	0.604	0.098	6.41	0
Bus1 * Inf7 <-Business*Information	0.654	0.661	0.07	9.312	0
Bus1 * Inf8 <-Business*Information	0.674	0.659	0.08	8.462	0

Table 5-101 shows the path coefficient and T-Statistic between two main variables (i.e., information driver & DPP), moderator (i.e., business & enterprise) and DPP, and moderation effect (i.e., business & enterprise * information) and DDP at a 95% of confidence level. Both path coefficient (-0.115) and T-value (2.846) of the moderation effect were higher than threshold limits, and there is no zero between the lower and higher limit of confidence intervals. Hence, it can be concluded that the T-statistic of the moderation path between the business & enterprise * information and DPP estimates the stability of the construct at the defined confidence interval. Thereby, it can be stated that the sub-hypothesis (H_{5-5}) has been approved statistically. However, the quality criteria of the developed construct have been checked to ensure the reliability and internal consistency of the construct have not been neglected.

Table 5-101-Path analysis of hypothesis 5-5. The business variable moderates the information driver and DPP.

	Path Coefficient (O)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Value	LLCI (2.5%)	ULCI (97.5%)
Business -> DPP	0.093	0.041	2.262	0.024	-0.011	0.155

Business*Information -> DPP	-0.115	0.04	2.846	0.004	-0.208	-0.05
Information -> DPP	0.883	0.024	36.984	0	0.829	0.921

Table 5-102 demonstrates the quality criteria for the sub-hypothesis, including Cronbach's Alpha, CR, and AVE. It can be observed that all criteria were higher than defined threshold limits which approved the reliability and internal consistency of the developed construct for the sub-hypothesis (5-5), and this sub-hypothesis has been certified. Although the R-squared value would not be considered merely to evaluate the model's fitness for the collected data, considering the R-squared value alongside the path coefficient and T-value can produce a reasonable prediction about the hypothesis model. R-squared has been computed and reported for the DPP variable to determine how the fifth sub-hypothesis and its developed construct can strongly estimate the variance. By considering the T-Value (2.846) of the moderator path (business & enterprise * information → DPP) at a 95% confidence interval and R-squared value (0. 829), it can be concluded that the developed construct for the sub-hypothesis (H_{5-5}) was fitted to the collected data and DPP can be explained 82.9% of the variance.

Table 5-102-Quality criteria of hypothesis 5-5 construct. The business variable moderates the information driver and DPP.

	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)	R-Squared
Business	0.809	0.869	0.624	---
Business*Information	0.942	0.945	0.521	---
DPP	0.892	0.925	0.757	0.829
Information	0.920	0.944	0.807	---

Table 5-103 shows the discriminant validity based on the Fornell-Larcker criterion of sub-hypothesis 5-5. As explained in chapter 3 for PLS-SEM path analysis, the square root of AVE would be higher than the correlation coefficient between the variables to satisfy the Fornell-Larcker criterion. The developed construct based on the definition of the fifth sub-hypothesis 5-5 has created an acceptable range of discriminant validity.

Table 5-103-Discriminant validity of hypothesis 5-5 construct based on the Fornell-Larcker criterion.				
	Business	Business*Information	DPP	Information
Business	0.791			
Business*Information	0.03	0.722		
DPP	0.081	-0.257	0.870	
Information	-0.01	-0.181	0.901	0.898

In conclusion, the quality criteria, discriminant validity, composite reliability, path coefficient, T-statistic, and R-squared values were shown that the research construct of the third sub-hypothesis (H_{5-5}) was fitted to the applied data. The relationship between information driver and DPP is moderated by the business & enterprise factor for the industrial clusters, and therefore, the sub-hypothesis (H_{5-5}) was supported.

5.14 Concluded remarks of CFA and SEM

Chapter five was designed to examine the proposed construct of this study. The proposed construct has been developed with 67 measures in 10 different variables, including five factors, three moderators, DPP and TSCV. According to the preceding literature review, five main hypotheses and twenty sub-hypotheses were initially suggested based on the proposed construct. This study's primary analyses, including CFA and SEM, were carried out using SmartPLS (V3). The quality criteria of the construct and variables were checked after each round of analysis, including AVE, CR, and Cronbach's alpha. Within the CFA, after each round of analysis, the unacceptable measures (i.e., indicators) were removed from the construct to enhance the reliability, internal consistency, and validity of the collected data and final construct. At the end of the CFA study, the transportation variable was removed from the construct because its number of validated measures was less than three. Hence, one of the leading hypotheses (i.e., hypothesis 4) and its sub-hypothesis were removed from the final construct. Figure 5-35 demonstrates all conducted analyses and considered quality criteria within CFA and SEM. The construct based on the four main hypotheses and their 16 sub-hypotheses were analysed using SEM. The path analysis of the main hypotheses and sub-hypotheses were analysed using bootstrapping test by selecting the path weighting scheme. It was determined that all main hypotheses had T-statistics higher than$|\pm 1.96|$) at 95% level of confidence.

Moreover, 16 sub-hypotheses have shown a satisfactory level of path analysis. The quality criteria were analysed after each round of each analysis. Table 5-104 summarised the list of final hypotheses and sub-hypotheses achieved after CFA and SEM analyses. As discussed, the transportation driver was removed from the construct, and therefore, all its sub-hypotheses were removed from the model and were highlighted by orange. All the approved hypotheses and sub-hypotheses were highlighted in green and light green, respectively. In addition, all of the rejected sub-hypotheses were highlighted in red.

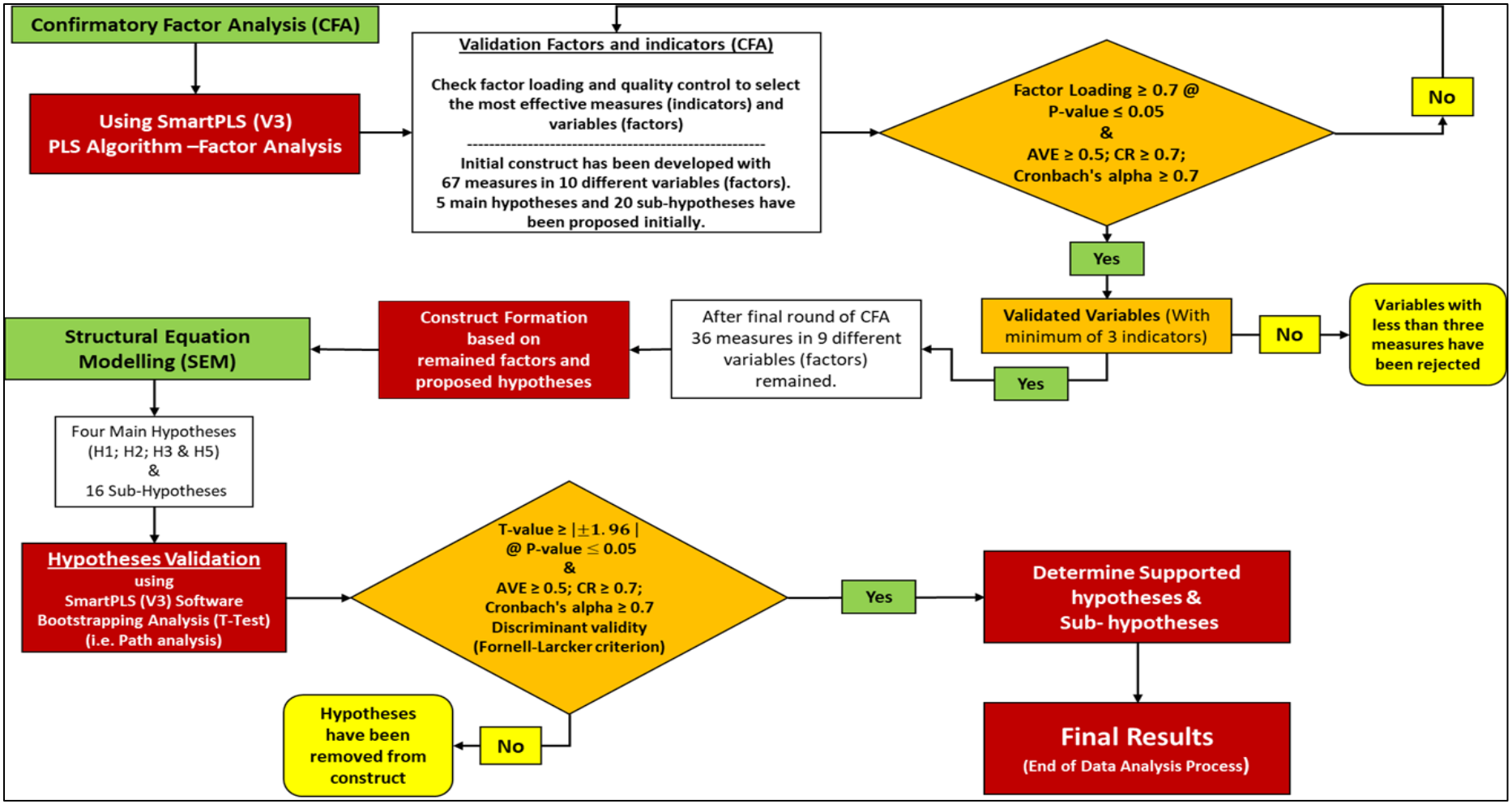


Figure 5-35- Demonstration of all conducted analyses and considered quality criteria within CFA and SEM.

Table 5-104-Summarised the list of supported - unsupported hypotheses and sub-hypotheses		
Code	List of Hypotheses and Sub-Hypotheses	Supported Yes/No
H1: SC drivers cause the change of DPP level in leagile SC.		Yes
H1-1	The production driver causes the change of DPP level in leagile SC.	Yes
H1-2	The location driver causes the change of DPP level in leagile SC.	Yes
H1-3	The inventory driver causes the change of DPP level in leagile SC.	Yes
H1-4	The transportation driver causes the change of DPP level in leagile SC.	Removed
H1-5	The information driver causes the change of DPP level in leagile SC.	Yes
H2: DPP adoption leads to better supply chain performance of the companies within industrial clusters.		Yes
H3: The relationship between supply chain drivers and DPP is moderated by the Basis & Foundation factor of the industrial clusters.		Yes
H3-1	The relationship between production driver and DPP is moderated by the Basis & Foundation factor of the industrial clusters.	No
H3-2	The relationship between location driver and DPP is moderated by the Basis & Foundation factor of the industrial clusters.	Yes
H3-3	The relationship between inventory driver and DPP is moderated by the Basis & Foundation factor of the industrial clusters.	Yes
H3-4	The relationship between transportation driver and DPP is moderated by the Basis & Foundation factor of the industrial clusters.	Removed
H3-5	The relationship between information driver and DPP is moderated by the Basis & Foundation factor of the industrial clusters.	Yes
H4: The relationship between supply chain drivers and DPP is moderated by the market factor of the industrial clusters.		Yes
H4-1	The relationship between production driver and DPP is moderated by the market factor of the industrial clusters.	Yes
H4-2	The relationship between location driver and DPP is moderated by the market factor of the industrial clusters.	No

H4-3	The relationship between inventory driver and DPP is moderated by the market factor of the industrial clusters.	Yes
H4-4	The relationship between transportation driver and DPP is moderated by the market factor of the industrial clusters.	Removed
H4-5	The relationship between information driver and DPP is moderated by the market factor of the industrial clusters.	Yes
H5: The relationship between supply chain drivers and DPP is moderated by the Business & Enterprise factor of the industrial clusters.		Yes
H5-1	The relationship between production driver and DPP is moderated by the Business & Enterprise factor of the industrial clusters.	No
H5-2	The relationship between location driver and DPP is moderated by the Business & Enterprise factor of the industrial clusters.	No
H5-3	The relationship between inventory driver and DPP is moderated by the Business & Enterprise factor of the industrial clusters.	Yes
H5-4	The relationship between transportation driver and DPP is moderated by the Business & Enterprise factor of the industrial clusters.	Removed
H5-5	The relationship between the information driver and DPP is moderated by the Business & Enterprise factor of the industrial clusters.	Yes

Chapter 6 Implications and Discussion

6.1 Introduction

Companies constantly pay attention to meeting customer needs to protect their competitive advantage over their competitors. One of the critical challenges in supply chain management is to formulate and implement suitable strategies. Therefore, measuring supply chain performance has become essential in today's business world (Deng et al. 2020).

Leagile strategies have been introduced as an effective SC strategy over the past decades to reduce waste, become cost efficient and develop flexibility in response to market shifts (Li et al. 2020). The Leagile approach transforms traditional SCs; the current competitive environment prompts SC managers to advance cost-efficiency and suppleness over their SC drivers (Galankashi and Helmi 2016). A company within a leagile SC can survive in challenging market conditions and gain a competitive advantage. They need to be innovative and ensure that their products deliver to market on time, in suitable quantities, and cost effectively. The lean strategy helps the companies identify and remove the unnecessary steps within their SC (Iyer et al. 2019). On the other side, agile SCs include quick, adaptive and robust companies capable of meeting ever-changing consumer demands and enjoying a competitive edge in the marketplace (Srinivasan et al. 2020). The leagile SCs combine the lean and agile strategies in which the lean thinking is followed on the upstream side of the SCs while agile thinking is implemented on the downstream side of the chain, and DPP acts as a border between the two (Nayak and Choudhary 2020). Due to the nature of today's products and services formed by several components from a combination of standard and innovative parts, the leagile strategy is essential for companies to survive in the marketplace (Bhamra et al. 2020a).

This study analyses the leagile strategy of three SCs, including furniture, agriculture machinery and equipment, and trout fish. The landscape of their industry is mature, characterised by low profit margins, high entry costs, limited market growth, and high competition between companies in the marketplace. Indeed, the companies within the cluster face increased pressure to grow the production scale while they remain highly fragmented with a disproportionate share of small companies. For example, in our case study in the north of Iran, only %3 of all companies had more than 100 employees. Despite that %89 of the companies surveyed in this study have more than five years of history and were identified as SMEs. Also, the environment of these industries is associated with high fluctuation in demand and sales growth for different

product categories. For example, with the mechanisation of the rice production process in northern Iran, the need for rice machinery and equipment has increased compared to garden products (Habibi et al. 2019). Significant variability in the cost structure, value-added and profitability, labour productivity of companies, and differences in the market prospects convinced the companies to rethink their SCs strategies and collaboration level within industrial clusters.

Furthermore, standard technologies, flexible production machines and facilities, access to FDIs (Foreign Direct Investments), and switching costs between different groups of products (for example, rice field machines versus gardening machines, bedrooms and living room furniture, or other breeds of fish) enable companies to diversify their product lines across a full range of final products. In this way, they can increase their profit by changing market segments according to the market's demand patterns (Lee et al. 2011). They need to have an appropriate SC strategy to achieve this capability. Consequently, this study seeks to evaluate the effective implementation of leagile SC and analyse the effect of its implementation on the SCs' performance of these companies within industrial clusters.

The companies were chosen among three industrial clusters in the north of Iran. The main reasons for selecting these three industrial clusters were listed as follows:

1) Most companies within these three industrial clusters are SMEs that adopt 'simple' business development strategies and their SCs.
2) Most of these companies are old and have traditionally formed their collaboration over the years. They need to know whether the leagile SC can help them increase profits and strengthen their cooperation in SC.
3) Different ability or willingness in the companies to develop leagile SC in the light of their profit, size, and experience. In other words, there is a significant difference in companies' production and competitiveness capability.

Therefore, they need to know which and how the SCs' drivers can help them to promote network integration and increase operational capabilities. So, this study analyses the SC drivers' effect on implementing leagile strategy for companies within industrial clusters. This is important because most members of the companies' SC are also members of their industrial cluster.

Therefore, the company's level of cooperation in its industrial cluster affects the way the company interacts within the supply chain. Generally, four factors stimulate the company to be engaged in an industrial group, including 1) clustering of companies in a particular geographical location can lead to advance proximity to original large suppliers or customers, 2) Access to resources in a geographical location for the companies (for example, High demand for agricultural machinery and equipment due to extensive agricultural lands and Orchards), 3) access to technology, knowledge, and skilful labour in a specific region, 4) existence of a particular industrial activity in a specific location which attracts relevant industries as suppliers or distributors (Petrenko et al. 2019; Claver-Cortés et al. 2020).

Morosini (2004) defined an industrial cluster as:

"*An industrial cluster is a socioeconomic entity characterised by a social community of people and a population of economic agents localised nearby in a specific geographic region. Within an industrial cluster, a significant part of both the social community and the economic agents work together in economically linked activities, sharing and nurturing a common stock of the product, technology and organisational knowledge to generate superior products and services in the marketplace*"

(Morosini 2004)

Companies' relationship within an industrial cluster is formed based on the economic and social communities; their effect should be examined on the performance of the leagile SCs. In the leagile SC literature, the scholars examine only companies' relationships within the SC network. To my knowledge, no research has studied the impact of companies' relationships within industrial clusters, including economic and social (that might be stronger than relationships within SC network), on implementing leagile strategy. In addition, this study has tried to test the impact of implementing a leagile strategy on the SC performance of the companies within the industrial cluster. Various measures and metrics were extracted to measure the SCs' drivers, industrial cluster factors, SC performance, and DPP by reviewing the literature.

This study presents how SC managers could trade between lean and agile strategies to enhance the total supply chain performance. To this end, the relationships between SC drivers, DPP, and SC performance have been analysed for the companies within three industrial clusters. Christopher and Towill (2000) classified the leagile implementation methods into three methods for integrating lean and agile strategies and taking the advantages of leagile SC, including DPP, Pareto curve, and 'base' and 'surge' demands methods.

The Pareto curve (80:20 rule) method categorises products into two main categories: the first category is 20% of the products accountable for 80% of total revenue. This line of products is known as fast-moving goods with relatively stable and predictable demand. Therefore, the products should be produced per lean philosophy (Make-to-stock) to facilitate cost-efficiency and efficient replenishment. Meanwhile, the remaining line of products, which accounts for 80% of total output, should follow agile thinking. These products are known as slow-movers with attributes such as high fluctuations in demand pattern and short life cycle, prompting the producers to generate supply only when the orders are received (make-to-order).

Another method for implementing a leagile strategy is the demand pattern, called 'base' and 'surge' demands. Base demand can be estimated by historical data, while surge demand is unpredictable due to the dynamic characteristics of marketplaces. So, in leagile SC, the Base demand is produced with a lean strategy to decrease the cost. In contrast, surge demand responds with more flexibility, resulting in a higher production cost compared to the Base demand.

DPP method deploys the lean strategy up to an appropriate point along an SC and implements agile strategy amongst remaining downstream companies up to the marketplace; at this point, the activities appertaining to forecast-driven scenarios at the upstream and those associated with order-driven scenarios intersect (Bhamra et al. 2020a).

Among the methods of implementing a leagile strategy, the DPP method was analysed in this research. Due to the nature of companies in industrial clusters, the DPP method promises to be more efficient than the other methods. As described in the paragraph above, the companies surveyed have unpredictable markets with variable demand volumes and rapidly changing customer needs. In addition, some researchers in literature like Christopher and Towill (2000); Mason-Jones et al. (2000) emphasised that the Pareto curve and 'base' and 'surge' demands methods are effective methods for implementing the leagile strategy in SC which are located in a low-cost area with cheap labour and energy cost as well as predictable demand for a part of their production. The companies can't separate products or demand based on the first two methods. The DPP allows them to use a lean strategy to a certain point along with the SC and an agile strategy from that point to the market. As a result, this study focuses on analysing the effect of the leagile strategy on SC's performance, which was implemented based on the DPP method. To this end, a model and hypotheses are proposed and tested by SEM coded in the SmartPLS V3 path modelling software package. First, the proposed model was modified by removing the measures with low factor loadings. The quality criteria were assessed against the thresholds referred to in the literature, and they have been found within the acceptable level.

Therefore, the analysis outcome could address the developed hypotheses and model. In the following sub-sections, the main finding of this study has been discussed, including the relationship between SCs' drivers and DPP, DPP and SC performance, and moderating effect of industrial clusters factors on the relationship between SCs' drivers and DPP (i.e., leagile implementation). The results showed a positive and significant impact of SCs' drivers on DPP in leagile SC and DPP on the SC performance. While the moderating effect of industrial cluster factors on the relationship between SCs' drivers and DPP was negative. The following sections will discuss the findings of this study based on the elements of the proposed model in detail.

6.2 Information sharing and DPP

Information flow in SC is a mechanism that facilitates coordination among SC members, which enables synchronisation between production scheduling, distribution planning, and inventory control (Raweewan et al. 2018). Chen et al. (2019) indicated that the increase in information sharing between the partners decreases the cost of inventory, production, and distribution. According to (Datta and Christopher 2011), members of the SC coordinate their processes through feedforwards/backward information-sharing mechanism. One of the dynamics of SC optimisation is enabled by information sharing to make informed decisions regarding production planning, assigning capacity, order processing, and material planning (Özer and Zheng 2017). Panahifar et al. (2018) emphasised that the lack of information sharing in an SC could lead to chaotic behaviour, panic, uncertainty, and an increase in preventable costs. One of the significant issues in SC is demand-order variability. This phenomenon is referred to as the "bullwhip effect", when the order variability received by the supplier exceeds the actual demand variability, reflecting the distortion and amplification of demand in an SC. The passage of information can minimise the detrimental effect of the bullwhip effect throughout the chain. Also, Hofmann (2017) argued for evident and streamlined information flow through coordination between the entities within a chain to simplify the material flow.

The extent of information sharing varies and depends on the nature of a business within a chain concerning outsourcing and the level of trust amongst the partners. Members always risk sharing sensitive information such as manufacturing scale, production schedule or inventory level (Özer and Zheng 2017). However, the lack of trust is an essential factor and is still considered an SC risk. Nevertheless, contemporary SCM practices encourage building cooperative and meaningful long-term relationships among partners of SC, urging them to be

willing to share risks reasonably. This is achieved by demonstrating the partners' persistent and positive attitude over an extended period. Industrial cluster coordinators always establish a deep connection between the cluster member companies. Efforts to create the structure of industrial clusters promote trust and interaction between companies. Companies within an industrial cluster are always encouraged to share accurate and timely information.

Consequently, information sharing gains the second-highest score among other SCs' drivers in this study.

Among the SCs' drivers, the effect of information drivers was significant (i.e., PC=0.902 and TV=47.206). The results have shown that the companies within industrial clusters can fit leagile strategy by finding the appropriate DPP over their SC based on the Information Technology/Information and Communications Technology (IT/ICT) development and partner's commitment and trust level (inf 1, inf 3, inf 7, and inf 8) (Zhang et al. 2016; Raweewan et al. 2018). On the other hand, a higher score in IT/ICT and a partner's commitment and trust level are necessary for adapting a leagile strategy (Zhao and Li 2018). Dolgui et al. (2020) emphasised that SC managers can trade off efficiency and responsiveness by developing digital technologies. Indeed, these technologies enable SCs to smoothly share information over the entire network and increase the level of companies' collaborations. Furthermore, Ivanov et al. (2019a); Ivanov et al. (2019b) introduced supplier collaboration portals as a necessary tool for sharing information (such as early warning signals, advanced selling notices and supply monitoring) over an SC. The portal could help the SCs' manager implement leagile strategy effectively and build the resilience of SC. Wong et al. (2015) recognised trust as a mutual behaviour of companies in SC operations and processes.

Khan et al. (2018) examined the effect of uncertainty on the trust among companies within SCs. They found that decreasing tension could increase confidence among companies in an SC. Also, they demonstrated that information sharing and trust positively impact the performance of SCs in terms of economic, environmental, and social dimensions.

According to the results of confirmatory factor analysis, five measures of the information sharing factor have been confirmed for evaluating the proposed model and hypothesis, including:

- Companies to share more accurate information with their partners within the industrial cluster to respond to customers' changing needs.
- The development of IT provides opportunities for companies to increase the level of information sharing within an industrial cluster.

- IT enables the companies to open up to new opportunities for increasing value through information sharing within the supply chain.
- Trust among the partners within the industrial cluster has removed obstacles to information sharing between partners.
- Partner's commitment within the industrial cluster leads the company to share accurate information, which indicates an elevated level of information sharing.

Trust in an SC could be defined in many ways. According to its generic sense, it means a willingness of a company to take a risk or expose itself to other companies (Panahifar et al. 2018). In this study, trust implies the desire of the companies within the industrial cluster to share accurate information in a real-time manner. Panahifar et al. (2018) evaluated relationships between information sharing and trust and their importance for effective SC collaboration and, in turn, its impact on the companies and SC performance. Their results showed that trust, the level of IT development among companies within SC (information readiness) and security could improve SC performance. In this study, based on the confirmed measures, commitment, trust, IT development, and understanding of the importance of information sharing are the most important measures for evaluating information sharing factors. Indeed, the SC's managers and industrial clusters' coordinators should pay more attention to these measures to deploy DPP for implementing leagile strategies in their SCs.

6.3 Production and DPP

In a leagile SC, the production is attained through amalgamating the lean and agile production system, functioning jointly in a continuum with a designated differentiation point (i.e., DPP). This strategy aims to lead the SC to market exploitation opportunities cost-efficiency and flexibly. The efficiency of the production facilities in the upstream side of a leagile SC is achieved through lean implementation to minimise waste or Muda by eliminating unnecessary production, unnecessary processes, and overproduction. Based on the practical perspective, effective products should be developed in leagile SCs by 1) eliminating bottlenecks to reduce unnecessary delays in production and 2) designing efficient production layouts to reduce lead time and enhance capacity utilisation. On the other hand, efficiency directly affects Production in different ways. In leagile SC, the production should ensure continuous/sustainable product quality improvement and minimise production defects. According to the responsiveness feature of the leagile SCs, the flexibility of the production facility and the product type on the

downstream side of the SC is an essential factor in production. Production flexibility refers to the capability of the manufacturing line to cater to fluctuations in production processes, the scale of production and the diversity of the product's range. In addition, the companies in the leagile SC should be able to customise their processes for facing unpredictable situations of the marketplaces. However, this could be potentially problematic for the manufacturers and result in a higher cost of production as it requires additional production adjustments and processes. Therefore, enhancing the capabilities of the manufacturer/assembler on the downstream side of the chain to respond to the market shifts by producing various products with numerous production processes and technics to accommodate changes in demand within the marketplace is imperative for the successful implementation of a leagile SC.

In addition, changes in customer needs occur very quickly. For example, customers always look for new and updated designs in the furniture industrial cluster. So, companies should be able to produce new products based on customer needs in different groups. In addition, product demand changes seasonally. In the furniture industry cluster, the demand for household furniture increased a lot before the beginning of the New Year (Persian New Year). Demand also changes seasonally for companies' agricultural equipment and industrial machinery cluster members.

Customers' needs are shifting rapidly and according to the time of planting crops in different product groups. For example, the demand for gardening equipment increases in the winter, while rice machines and equipment demand rise in the summer. The need for fish products is higher for the industrial trout cluster companies. Customer demand for purchased processed products with new packaging is also increasing. Unlike in the past, customers are looking to buy fish with certain weights, sliced, flavoured, and packaged. Another point of consideration for fish companies is the significant difference in customers' tastes in different regions. Hence, they have faced a variety of baskets of demand from other areas. As a result, the companies studied in this study are always affected by market demand fluctuations.

This research can give these companies a clear vision of implementing a leagile strategy. The results can also show them what SCs' drivers they must focus upon.

The company's manager within industrial clusters could implement the leagile strategies and improve the SC performance by considering their production operations. Results demonstrated that due date, demand level, waste cost, utilisation rate, and production variable cost significantly and positively impact the leagile implementation (Dong et al. 2019; Ben-Ammar et al. 2020). Chan et al. (2009) suggested that the companies can benefit from the advantages

of leagile through integrated production planning and scheduling. This way, companies could forecast demand, increase utilisation, and decrease the due date. In addition, the pull distribution system in leagile strategy helps the SCs manage production by balancing raw material and final product inventory at DPP over an SC (Chan et al. 2009). According to the results, the SCs' manager should pay more attention to the due date, cost, waste, and demand in production driver to successfully implement the leagile strategy based on the DPP method. In other words, the position of the decoupling point should be moved based on the production measures, including the due date, cost, waste, and demand for products. For example, Nieuwenhuis and Katsifou (2015) argued that the DPP could be moved to the downstream side of the SC, where the product's due dates are short, and production cost is low. The companies within these three industrial clusters should focus on the new manufacturing and production technologies to achieve these goals. For example, leagile production and manufacturing need advanced manufacturing methods like abrasive jet machining (AJM), electric discharge machining (EDM), electrochemical machining (ECM), and automated guided vehicle systems (AGVS), CAD/CAM, and CAE to make quality products. Virmani et al. (2018) reviewed leagile manufacturing as one of the dominant research projects in operation management. Their finding showed that leagile manufacturing is unlike pure lean or agile and is distinguished by the DPP feature.

Suitable knowledge and implementation of leagile strategy in companies' results in improved profitability of a company, better customer relations, enhance quality and sales, increase the resources consumption, and decrease the inventory cost and all other costs which does not add value to the final product.

6.4 Location and DPP

Location decision plays a critical role in the effectiveness and efficiency of the SCs. Indeed, deciding on facilities' location and determining material flow within the SC network affect other SCs' drivers, such as inventory and transportation (Emelogu et al. 2019). Hugos (2018) argued that location, inventory, and transportation decisions are fundamental drivers in logistics management and essential in advancing SC performance. Rather than finding an appropriate geographical location for the facility, the location decision problems address the SC's activities assigned to the locations. The SC managers should carefully consider the location of their operations (e.g., production, holding, distributing sites) within SC.

Many scholars (Tlahig et al. 2013; Lara and Grossmann 2016; Emelogu et al. 2019) studied the effect of location policy on the performance of SCs. Their finding demonstrated that centralising

the facility's location within SC increases the performance of the SCs from an economic viewpoint. In contrast, the decentralised policy in allocating activities would improve the service level and responsiveness of SCs. Several measures must be considered, including the fixed and variable costs of the activities within SCs to decide on the facility's location, i.e., production and transportation, infrastructures and services, and access to skilled labour. After determining the location of facilities within the SC, the material and information flow from supplier to the customer should be determined. Also, the location decision represents the basic strategy for designing SCs (Farahani et al. 2019). the findings of this thesis show that companies can manage their SC performance by taking informed location decisions. Results demonstrated that the location factor impacts the implementation of the leagile SC by the DPP method. In addition, the results have shown that a suitable location site could facilitate the leagile strategy adaption and further improve the TSCV through: i)Decreasing the company's cost, including land, energy, infrastructure, services, telecommunications, and labour, ii) Increasing the availability and access to educated and skilful workforce, iii) Providing advantages of the laws and regulations stability and tax policies.

Indeed, it can be stated that finding an appropriate location can reduce various costs such as land, energy, bureaucracy and regulations, and labour. Galankashi and Helmi (2016) evaluated the relationship between the facility's location and leagile implementation. Their results demonstrated that SCs managers should follow a decentralised facility location strategy aligned with DP's position, ensuring the site of the facilities in leagile SC provides a collaborative environment (Purvis et al. 2014). Consequently, the companies within the industrial cluster located in a close geographic dispersion can potentially adopt a leagile strategy in their SC.

6.5 Inventory and DPP

Inventory management in leagile SC aid the companies in a way that leads to cost-effectiveness and responsiveness to reduce costs while taking proportional actions against changes within the marketplace. JIT is a practical approach for delivering components, modules, and final products on time with the aim of inventory minimisation through reliance on suppliers' and carriers' capability to procure the desired quantity within a fixed time frame. Therefore, leagile SC should embed Sourcing Flexibility (SF) and Vendor Flexibility (VF) strategies concerning its inventory. The SF confers to the capability of the system's operator to reshape and reconfigure the SC through the selection and de-selection of vendors; this is for the formation of a more comprehensive supplier base which leads to greater market adaptability and resiliency (Purvis et, al. 2014).

The VF refers to the ability of each vendor to be independently flexible. Each supplier should have own internal flexible inventory system regarding every SC node, connected to warehousing, transportation, and manufacturer (Purvis et al. 2014). According to the findings of this study, the companies in the survey prefer to reduce the amount of the final products in their warehouses. The companies have the potential to use shared warehouses with their suppliers and vendors (or distributers) within their industrial clusters. Since the companies are located within a close geographical location, they can have transferred warehouses for raw materials and final products. Shared warehouses between companies within industrial clusters decrease inventory costs and increase supply chain profits.

In addition, extensive horizontal and vertical relationships within an industrial cluster help the companies follow SF and VF approaches. Because of the horizontal connections in the industrial cluster, there are suppliers with similar capabilities. On the other hand, various selling channels will be available (a company in a higher industrial cluster or end-users). Thus, it can be concluded that companies within industrial clusters have a high capability in SF and VF approaches through internal relationships within the industrial cluster and shared warehouses. Having such relationships helps them control the inventory of raw materials and the final products.

Furthermore, on the downstream side of a leagile SC, the selection and deselection process of suppliers should be carried out under the consideration of unpredictable demand and instability, and decision-making is carried out under the supervision of the managers to assess the supply and demand in the marketplace to select and deselect suppliers. As mentioned in section 6.3, the companies within these three industrial clusters encounter high demand uncertainty and fluctuation in orders. In this study, the company's high inventory level can cause losses and reduce profits in the SC. For this reason, a leagile strategy is a fundamental approach for the companies within industrial clusters. They can use the benefits of the leagile SC to control their inventory levels and deal with market complexities by designing flexible communication channels (e.g., flexible vendors and suppliers).

Handling procurement and costs associated with the function of an inventory facility and the location of an inventory is a strategic challenge for the SC members. To attain efficiency and flexibility in a leagile SC's stock based on the DPP method, the companies should optimise their operation on both sides of SC. On the upstream side of the SC, the main aim is to generate a high utilisation rate. Since this stage of the SC production is based on the forecast, all the relevant order information is passed directly to the producer for more accurate extrapolation, so

no excess stock is held in the inventory for the upstream entities. At the position of the DP, the companies should have sufficient inventory as a strategic buffer to respond to market changes effectively. Finally, on the downstream side of the SC, no finished products are held as inventory in the manufacturing plant(s); once the customisation/assembly is taken place, the final products are dispatched to the retailers or the end customers directly (Goldsby et al. 2006a). As a result, in a leagile SC, the critical stocking point is held at the DPP to balance responsiveness and costs associated with inventory. The manufacturer(s) downstream delays the customisation/assembly as long as possible until the exact attributes/scale of the product's requirement is identified (Wadhwa et al. 2009; Marodin et al. 2017). The results show that the companies within industrial clusters could effectively develop a leagile strategy by controlling the final products' inventory level.

Results of CFA show that optimising the order points, final product inventory level, holding cost, and inventory turnover are the most important measures for evaluating the effect of inventory driver on the leagile implementation by the DPP method. Order point refers to the inventory amount to place an order, which is used in inventory management models. Indeed, the companies within the industrial clusters need to find optimum inventory levels and ordering times. In addition, they should inform their suppliers and vendors about the stocking level to avoid any loss of sales or backorder or tock obsolescence (Mousavi et al. 2019).

As one of the findings of this study, the ordering points are different according to the position of the DP. For example, the company could increase the ordering point on the upstream side (from supplier to DPP). While at DPP and downstream side, the inventory level should be as balanced as possible. Another critical measure of inventory driver is Inventory turnover. It indicates how a company sells and replaces its stock of goods during a particular period. The inventory turnover ratio formula is the cost of goods sold divided by the average inventory for the same period. This study showed that the inventory turnover is high in the companies within industrial clusters. Because the companies within industrial clusters are close to each other and a strong relationship has been established between them, the ordering cost is low, and the due date of orders is short. So, the company's inventory turnover was high. These advantages help the companies within industrial clusters implement an effective leagile strategy by controlling their inventory level.

6.6 DPP and SC performance

In a leagile SC, the marketing advantage of customisability aspect of production, and make-to order at the downstream side of SC is through the implementation of 'form postponement' on

DPP. To postpone the manufacturing and production until customers place an order and stipulate the product's exact specification and the order's volume, the component/modules will be prepared at the central stocking point, ready to be customised. It is also important to point out the postponement regarding manufacturing here; according to (Virmani et al. 2018), demand estimation becomes more accurate as the postponement in production increases. However, there should be a limit to the extent of postponement. The excessive surge in postponement level leads to higher lead-time and cost of production (Purvis et al. 2014), which is a sign of inefficiency and not aligned with leagile SC philosophy; thus, excessive postponement in production must be avoided.

Previous research shows that implementing a leagile strategy can positively or negatively affect SCs' performance. As emphasised by other researchers (Nieuwenhuis and Katsifou 2015; Shahin et al. 2016; Aktan and Akyuz 2017), unsuitable DP positions will reduce supply chain performance. This study also shows that companies should increase SC performance by paying attention to production efficiency. Indeed, the wrong position of the DPP would decrease production efficiency.

In addition, according to the results of CFA, the DPP 2 measure has been approved in this study to evaluate the DPP method. This measure shows the positive effect of production efficiency on SC performance. So, companies within industrial clusters should strive to use the DPP method to increase production efficiency. DPP 3 was confirmed as another measure of the DPP method for implementing leagile SC in this study. The companies should aim to hold the products in the work-in-progress state instead of final products (ready to be delivered). In a leagile SC, the critical stocking point is held at the DPP to balance responsiveness and costs associated with inventory. At this phase, standardised goods stay undifferentiated for as long as possible in the form of a strategic buffer (Bhamra et al. 2020a). The manufacturer at downstream delays the customisation for as long as possible at the inventory level until the exact attributes or scale of the product's requirement is identified. The customisation phase will initiate as soon as demand is realised and accepted. Once the customisation process is completed, the final products will be shipped out immediately as the order's details are known. As a result, no inventory (minimum inventory) can be kept in the form of finished products in the companies' warehouses.

Information sharing in the DPP method penetrates the chain as upstream as possible to improve the information quality and avoid demand distortion and the bullwhip effect. The IT acts as an agent facilitator to elevate demand information transparency and increase forecast accuracy,

resulting in postponement value enhancement (Chen et al. 2019). Advancement of IT has yielded more value to postponement strategy by projecting data from downstream to upstream and vice-versa (Raweewan et al. 2018). The IT aids the upstream side of a leagile SC by receiving data concerning the amount of procurement required in the downstream side of SC, resulting in a higher precision forecast. In addition, companies on the upstream side of the chain are responsible for passing down accurate data to partners regarding their production planning and inventory level to companies closer to the end customers. IT aids the downstream side of a leagile SC by receiving order data and capturing the latest trend in a timely and accurate manner so the firms can postpone the final customisation stage until the actual orders are received, which leads to the attainment of a higher response rate towards market shifts. This study confirmed that the companies within industrial clusters should connect both sides of the DPP by developing ITC capabilities. Indeed, developing IT along SC provides numerous opportunities for companies to facilitate information sharing.

6.7 Moderating effect on the relationship between SC drivers and DPP

Porter (2000) defined industrial clusters as regional concentrations of interconnected companies with similar functions or associated industries. The main advantages of industrial clusters are knowledge and technology sharing, efficient transportation systems and infrastructures, and access to skilled workers (Lublinski 2003). Claver-Cortés et al. (2020) confirmed that industrial cluster strategies should build strong relationships and interactions among companies within the cluster. In addition, strategies should be able to conduct company outsourcing activities with other companies outside the industrial cluster. Indeed, the strategy of industrial clusters should support leading companies aiming to advance their economy and profit from the industrial cluster. Because with the growth of major companies within the industrial cluster, other small companies can also flourish. In addition, a comprehensive strategy is needed to develop industrial clusters considering issues such as collaboration and market. To the best of my knowledge, there is no research in the literature focusing on developing industrial clusters by considering the leagile strategy. This study surveys the companies within three industrial clusters to evaluate the effect of the SCs' drivers (production, inventory, location, and information sharing) on the leagile strategy implemented by the DPP method and the performance of the SC (in terms of cost, quality, lead-time, and service). The findings can help industrial clusters' coordinators, companies' managers, and SC managers to develop leagile strategies within industrial clusters. Rather than the relationships between SCs' drivers and DPP and SC performance, this study tests the moderating effect of industrial

clusters factors on the relationship between SCs' drivers and DPP. As one of the major research questions, by assessing the moderating effects of the industrial cluster on the relationship between SC drivers and DPP

To this end, the industrial cluster literature has been reviewed to explore its factors. Determining the elements of industrial clusters is a critical challenge for analysing their performance and capabilities. The success of industrial clusters could be analysed through effectiveness criteria such as goal attainment or the satisfaction level of companies. An effectiveness analysis provides insights into the ability of industrial clusters to reach goals at company and cluster levels. The effectiveness of industrial clusters is the same as the effectiveness of their companies and inter-organisational relationships, which are affected by various factors arising from industrial clusters' context, structure, and functioning mechanisms. The structures of the industrial cluster define processes within the cluster and regulate the relationships among companies and between companies within the industrial cluster and the cluster coordinators. The cluster structures form the cooperation among the companies within the cluster, determining their quality and strength and subsequently affecting the overall performance of the industrial cluster. While most research in industrial clusters has examined the effect of an individual factor on the success of industrial clusters, few researchers have focused on comprehensively identifying the factors affecting the success of industrial clusters.

In addition, most of the research was based on case studies to find the best experiences in managing industrial clusters. In contrast, less attention was paid to identifying the success factors of industrial clusters using quantitative methods (Gereffi and Lee 2016; Padalkar et al. 2019).

The results of the CFA confirm that the presence of solid suppliers within industrial clusters, the commitment of companies to high cooperation within the cluster, alignment of companies with the goals of industrial clusters, and the existence of a high level of reliability are the most effective measures to evaluate the success of the industrial cluster based on the business and enterprise factor. Also, access to foreign markets with high demand, constant sales policies, and connection to the local value chain of the producers are the most effective for evaluating market factors of industrial clusters. Due to the basis and foundation factor, financial resources, technological development, and internal and external environment control were the most notable measures. The results of this study propose the most important factors and measures for quantitatively evaluating companies' success within industrial clusters. Other research in the industrial clusters literature found similar results. For example, da Rocha et al. (2009) analysed

the export growth of two industrial manufacturing clusters. Their findings proved the role of leader companies (the large enterprises within industrial clusters) in leading the internationalisation process. Indeed, this is not possible for all companies within an industrial cluster to access foreign markets. The leader companies (generally the companies that produce the final products) should pave the way to access foreign markets. In another research, Bondarenko et al. (2016) emphasised that technological development and improving the financial system of companies within industrial clusters could help the companies to overcome different obstacles such as global economic instability, tools and mechanisms, lack of an effective method of public or private partnerships, and high geopolitical risks. After confirming the explored measures and constructs of the proposed model, the H3, H4, and H5 were tested. H3, H4, and H5 have been presented to analyse the moderating effects of industrial clusters factors between SCs' drivers and DPP. Results confirmed that the industrial clusters' factors directly affect the relationship between SC drivers and DPP (see Table 8). In companies with a higher score of SC drivers, the basis and foundation, market, business and enterprise have a lower impact on the DPP. While in the companies with the lower score of SC drivers, the moderating variables have a higher impact. To further investigate the moderating effect of the industrial clusters factors on the relationship between SC drivers and DPP, Simple Slope Analysis (SSA) has been used. Aiken et al. (1991) recommended generating a series of simple regression equations to realise the nature of the moderating variables. Cohen et al. (2014) used three values of the moderator: the mean value, the value is one standard deviation above, and the value one standard deviation below the mean to test the relationship between independent and dependent variables at different values of moderating variable. Figures 6-1, 6-2, and 6-3 represent the SSA for H3, H4, and H5. The X-axis is labelled as the SC drivers (independent variable), and Y-axis is labelled as a DPP (dependent variable). The green and blue lines show the effect of moderating variables (industrial clusters factors) with one standard deviation above and below the mean of the moderator, respectively. The red line shows the mean effect of the moderator variables. Comparing the three lines demonstrated that the impact of the moderating variables was strongest at the lowest level of SC drivers and DPP. The crossing points at the top right of the graph proved that the impact of moderating variables had declined the relationship between SC drivers and DPP with higher scores. Indeed, the results of the SSA confirm the negative path coefficient obtained by the bootstrapping method and are reported in Table 8 (i.e., negative direct impact of moderator variables). It can be concluded that the effect of the SC drivers on DPP is higher in companies with weaker members of their industrial cluster.

In addition, the SSA represented that DPP would be increased in companies with higher SC drivers (inventory, location, information, and production). Also, this test supported the H1 hypothesis and its sub-hypothesis.

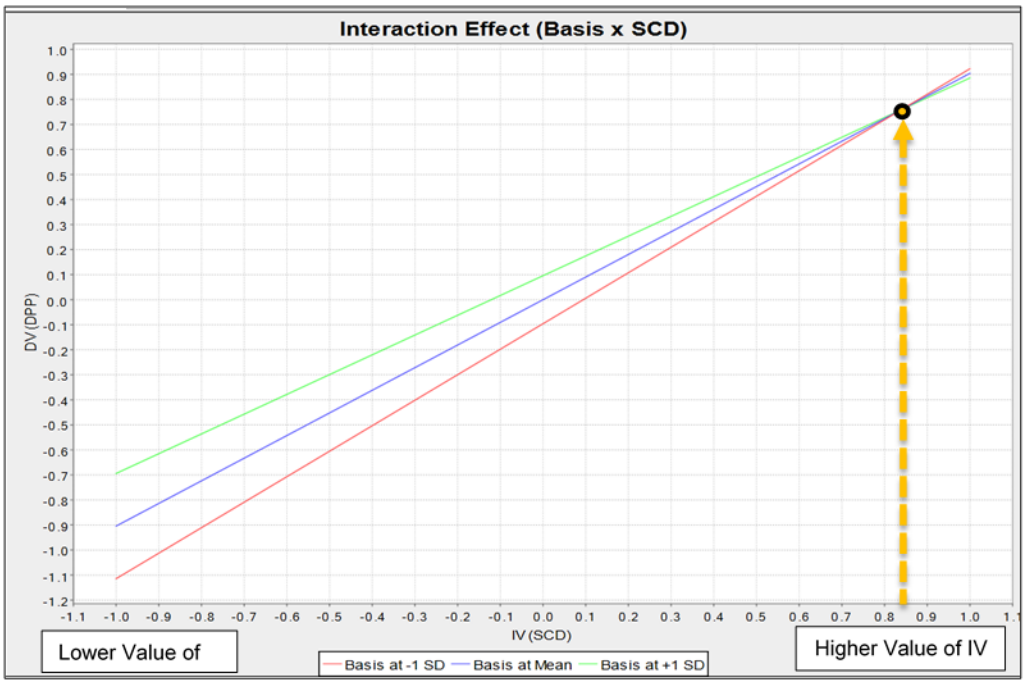


Figure 6-1 SSA for the interaction effect of basis and Foundation (basis*supply chain drivers) on the relationships between SC drivers and DPP.

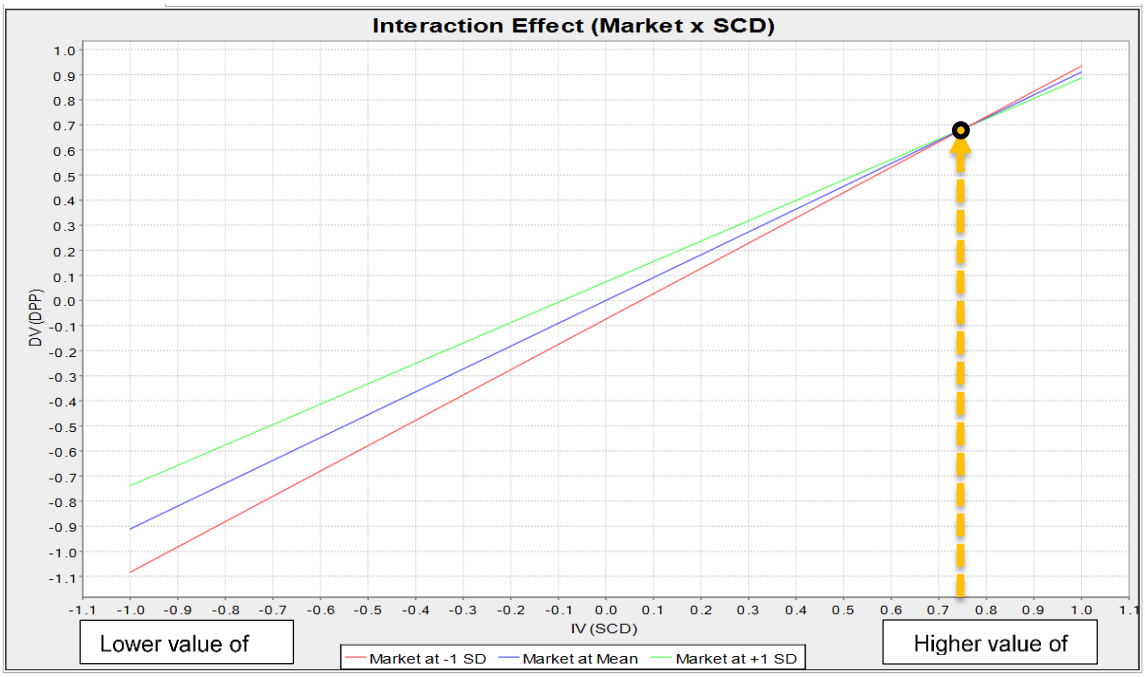


Figure 6-2-SSA for the interaction effect of Market (market*supply chain drivers) on the relationship between SC driver and DPP (H4).

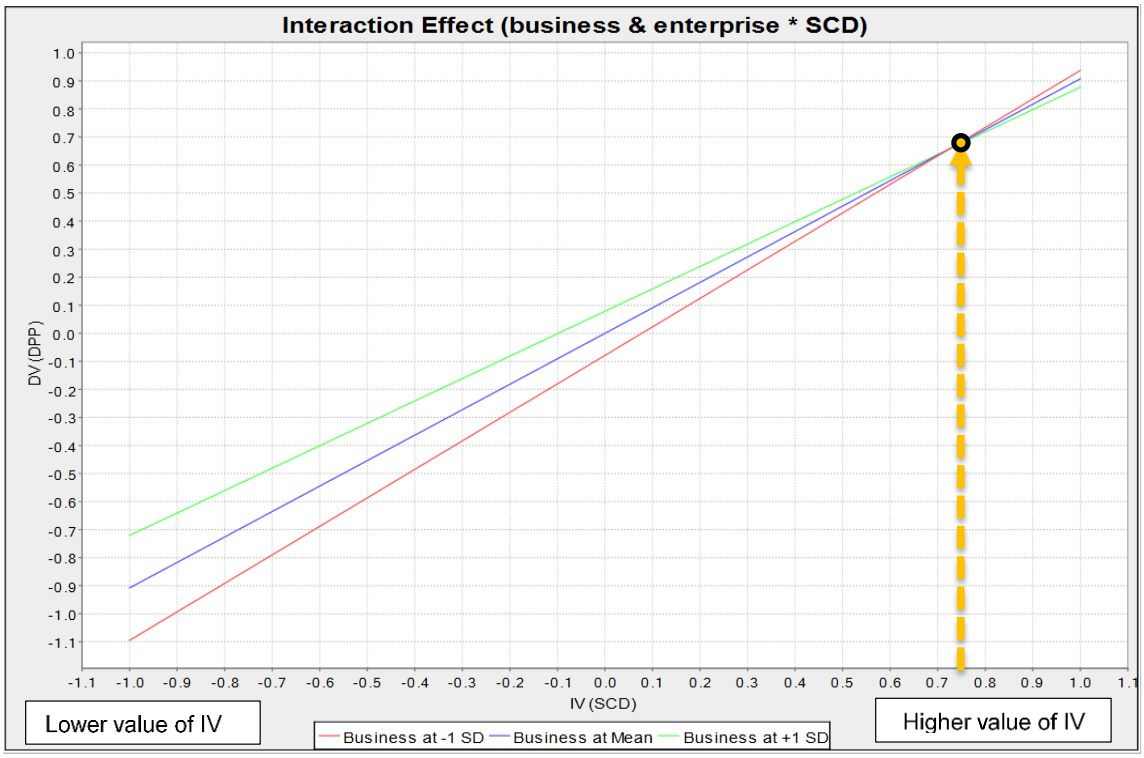


Figure 6-3- SSA for the interaction effect of Business and Enterprise (business*supply chain drivers) on the relationship between SC drivers and DPP (H5).

Regarding the moderating effect of industrial clusters factors, the result shows that companies who are lower in business and enterprise, basis and foundation, and market but have high SC drivers are more likely to adopt leagile strategy through the DPP method than those who have relatively higher business and enterprise, basis and foundation, and market with lower SC drivers score. This implies that industrial clusters factor themselves are not a hurdle for those companies who want to adopt a leagile strategy once SC drivers highly support them. Therefore, companies within industrial clusters may not need to have reservations about establishing or expanding their interactions with other companies in order to implement leagile SC startegy. Recognising that SC drivers are strong enough for companies to adopt a leagile strategy regardless of the company's position within the industrial cluster, companies should pursue tactics to build information sharing, location, inventory, and production capabilities. SC drivers are features and capabilities of inter/intra companies that must be aligned with leagile strategies for performance improvements.

Consequently, an SC can adopt a leagile strategy by enhancing SCs drivers' level compared to industrial clusters. In contrast, companies in the industrial cluster that do not have a robust supply chain (drivers score is low) should develop a suitable strategy by relying on inter-cluster communications and collaboration. As shown in figures 6-1 to 6-3, the moderating variable positively impacted the DPP score for the same supply chain driver score.

6.8 Managerial implication

This section analysed the relationship between SC drivers and DPP and evaluated the effect of DPP on SC performance from the managerial perspective. The SC managers and industrial clusters coordinators can use this research to enhance the company's performance within industrial clusters by adopting the DPP method. Results confirmed that the leagile strategy could help companies increase their SC performance in TSCV. In addition, companies within industrial clusters don't face obstacles to developing SC leagile strategy. In other words, although companies should strive to strengthen their position in their industrial cluster, industrial cluster membership was not recognised as an impediment to implementing a leagile strategy. In addition, it was clarified that:

- By breaking the due date into shortened slots and reducing the amount of demand instead of the extended due date, the company can reduce the inventory level and cost of the final products and respond faster to changes in customer demand needs.
- The company's interaction with other members of the industrial cluster and establishing reliable relationships can reduce production costs such as labour, equipment, and raw materials and improve operational efficiency. This way, companies can adopt the leagile strategy and improve SC performance by stimulating the production driver.
- The development of IT/ICT in the presence of reliability and commitment among the companies within the industrial cluster can effectively help companies implement the leagile strategy by creating new opportunities and rapidly sharing accurate and correct information.
- Access to foreign markets requires the development of information-sharing capabilities and adjusting to global industry standards. By facilitating the flow of information from foreign markets to the upstream members of the SC, companies can manage work-in progress inventory instead of holding the final products and customising the final products based on predetermined customer needs.

- The companies with low SC drivers' scores should build their network within their industrial cluster. In this way, they can improve the effectiveness of the DPP method and further the SC performance.

Chapter 7 Conclusion

7.1 Overview

The Supply Chain Management definition involves integration and coordination between production, distribution, and inventory management. Many companies pursue lean and agile SC strategies to reduce costs and improve customer demand to reach a competitive advantage. Shahin et al. (2016) defined lean manufacturing as a set of techniques such as Just-In-Time (JIT) and Total Quality Management (TQM), working together synergistically to create a high quality streamlined value chain. Conversely, the agile concept is about flexibility and rapid response to demand variation in a changing market environment, whether in product variety, volume, or mix (Christopher et al. 2001). Although both concepts are inherently different, they can be combined to form a total operational SC known as "leagile" (Naylor et al. 1999a).

Leagile strategy is a hybrid of conventional lean and agile strategies to help companies take advantage of both strategies in terms of efficiency and flexibility in SC (Bhamra et al. 2020a). However, effective implementation of the leagile strategy in SCs is one of the main challenges for SC managers. Fadaki et al. (2020) argued that a significant deviation exists between the companies' fundamental practices and the core leagile conceptual strategy. According to (Bhamra et al. 2020a), this gap has remained in literature, and scholars should develop appropriate techniques for properly implementing leagile strategy within SCs. So, this study aims to evaluate the relationship between SC drivers and DPP as a well-known method for implementing leagile strategy. This way, the companies could implement leagile effectively based on their SC features.

Successful implementation of SC strategies requires exploring the SCs' drivers related to the leagile strategy in SC. Hugos (2018) categorised all operations of the SC into four main categories: planning, sourcing, making, and delivering. He emphasised that production, inventory, location, transportation, and information are the five main drivers for providing final products or services to the markets. The capabilities and effectiveness of the SCs' strategies depend on these drivers. So, this study evaluates the effect of these SCs’ drivers on the DPP method. In this way, companies focus more on drivers to develop leagile Supply Chain. In other words, the companies find which drivers should be optimised based on the leagile strategy.

Industrial clusters are regions of interconnected companies with similar functions or associated industries (Porter 2000). The main advantages of industrial clusters are knowledge and

technology sharing, efficient transportation systems, access to infrastructures and skilful workers (Lublinski 2003; Speldekamp et al. 2020). In addition, the success of industrial clusters was credited to several key characteristics such as geographic proximity and intimate social relations, which helped reduce transaction costs and nurture trust, and the formation of informal networks, facilitating the flow of information, knowledge, and skills (De Marchi and Grandinetti 2014). Although lean, agile, and leagile SCs strategies have been studied in the SC literature, limited attention has been paid to analysing industrial clusters' effect on the relationship among SC drivers, leagile implementation, and SC performance. This study aims to examine the effect of SC drivers on the implementation of leagile strategy for companies within industrial clusters. To this end, the researcher studied those companies that develop leagile strategies based on the DPP method. So, the results could cover the literature gap by answering three questions including

1- What are the effects of SC drivers on DPP?
2- What are the moderating effects of the industrial cluster on the relationship between SC drivers and DPP?
3- How does DPP influence supply chain performance?

This research answered these questions by surveying companies within three industrial clusters: furniture, agricultural machinery and equipment, and trout fish. To this end, different measures have been identified to quantitatively evaluate the relationship between SC drivers, DPP, and SC performance. The study involved two hundred twelve experts of companies within three industrial clusters. In summary, Table 7-1 presents the sub-hypotheses tested in this study. Statistical analysis of the collected data from companies within three industrial clusters in the north of Iran supports 17 out of 25 hypothesises and sub-hypotheses.

Table 7-1-Summary of proposed hypothesises

Hypothesis		Supported
H1	SC drivers cause the change of DPP level in leagile SC	S
H1-1	The production driver causes the change of DPP level in leagile SC	S
H1-2	The location drivers cause the change of DPP level in leagile SC	S
H1-3	The inventory drivers cause the change of DPP level in leagile SC	S
H1-4	The transportation drivers cause the change of DPP level in leagile SC	N
H1-5	The information drivers cause the change of DPP level in leagile SC	S

H2	DPP adoption leads to better SC performance of the companies within industrial clusters	S
H3	The relationship between SC drivers and DPP is moderated by the Basis & Foundation factor of the industrial clusters	S
H3-1	The relationship between production drivers and DPP is moderated by the Basis & Foundation factor of the industrial clusters	N
H3-2	The relationship between location drivers and DPP is moderated by the Basis & Foundation factor of the industrial clusters	S
H3-3	The relationship between inventory drivers and DPP is moderated by the Basis & Foundation factor of the industrial clusters	S
H3-4	The relationship between transportation drivers and DPP is moderated by the Basis & Foundation factor of the industrial clusters	N
H3-5	The relationship between information drivers and DPP is moderated by the Basis & Foundation factor of the industrial clusters	S
H4	The relationship between SC drivers and DPP is moderated by the market factor of the industrial clusters	S
H4-1	The relationship between production drivers and DPP is moderated by the market factor of the industrial clusters	S
H4-2	The relationship between location drivers and DPP is moderated by the market factor of the industrial clusters	N
H4-3	The relationship between inventory drivers and DPP is moderated by the market factor of the industrial clusters	S
H4-4	The relationship between transportation drivers and DPP is moderated by the market factor of the industrial clusters	N
H4-5	The relationship between information drivers and DPP is moderated by the market factor of the industrial clusters	S
H5	The relationship between SC drivers and DPP is moderated by the B&E factor of the industrial clusters	S
H5-1	The relationship between production drivers and DPP is moderated by the B&E factor of the industrial clusters	N
H5-2	The relationship between location drivers and DPP is moderated by the B&E factor of the industrial clusters	N
H5-3	The relationship between inventory drivers and DPP is moderated by the B&E factor of the industrial clusters	S

H5-4	The relationship between transportation drivers and DPP is moderated by the B&E factor of the industrial clusters	N
H5-5	The relationship between information drivers and DPP is moderated by the B&E factor of the industrial clusters	S

7.2 Answer to the research question

The scope of this study is limited to companies that are members of the industrial clusters and produce furniture, agricultural machinery and equipment, and trout fish in Iran. In total, 212 completed questionnaires were collected. According to the results of the pre-analysis, Partial Least Squares have been used to test the proposed model and hypotheses. This section aims to wrap up the central questions of this research. So, a summary of the research questions addressed in this study are as follows:

What is the effect of SCs' drivers on implementing leagile strategy by the DPP method?

This study aims to find the relationship between SC's drivers and leagile strategy by surveying companies within three industrial clusters. The results (path coefficient= 0.925 and T-value= 60.467, p-value=0) confirm that the SCs' drivers have a positive direct impact on the DPP score, and hypothesis H1 was supported. It means that the score of the leagile strategy was higher in companies with more effective SCs' drivers (higher value of SC). ***The SCs' drivers directly affect implementing the leagile strategy through the DPP method in companies within industrial clusters***.

What is the effect of production on implementing leagile strategy by the DPP method?

The results (path coefficient= 0.887 and T-value= 38.465, p-value=0) confirm that the production driver positively impacts the DPP score, and hypothesis H1-1 was supported. It means that the score of the leagile strategy was higher in companies with more effective production capabilities. ***The production driver directly affects the implementation of the leagile strategy through the DPP method in companies within industrial clusters***.

What is the effect of location on implementing leagile strategy by DPP method?

The results (path coefficient= 0.895 and T-value= 44.443, p-value=0) confirm that the location driver has a positive direct impact on the DPP score and hypothesis H1-2 was supported. It

means that the score of the leagile strategy was higher in companies with more effective location strategies. ***The location driver directly affects the implementation of the leagile system through the DPP method in companies within industrial clusters***.

What is the effect of inventory on implementing a leagile strategy by the DPP method?

The results (path coefficient= 0.931 and T-value= 59.165, p-value=0) confirm that the inventory driver has a positive direct impact on the DPP score and hypothesis H1-3 was supported. It means that the score of the leagile strategy was higher in companies with a more effective inventory management system. ***The inventory driver directly affects the implementation of the leagile system through the DPP method in companies within industrial clusters***.

What is the effect of transportation on implementing leagile strategy by DPP method?

The transportation factor has been removed from the final construct due to the remaining two measures (indicators) and caused a negative degree of freedom. Therefore, the transportation driver was removed due to CFA, and hypothesis H1-4 was not supported. The study can't conclude that score of the leagile strategy was higher in companies with more effective transportation infrastructure.

What is the effect of information on implementing leagile strategy by DPP method?

The results (path coefficient= 0.902 and T-value= 47.206, p-value=0) confirm that the information driver has a positive direct impact on the DPP score and hypothesis H1-5 was supported. It means that the score of the leagile strategy was higher in companies with more effective information-sharing infrastructure. ***The Information driver directly affects the implementation of the leagile system through the DPP method in companies within industrial clusters***.

Which SCs' driver has the highest effect on implementing the leagile strategy?

This study shows that, except for transportation, four other drivers, including inventory, location, production, and information sharing, directly affect the implementation of leagile strategy in companies within industrial clusters. Information sharing (t-value=47.206), inventory (t-value=59.165), production (t-value=38.465), and location (t-value=44.443) were the most effective drivers respectively.

Would the DPP method lead to better supply chain performance of the companies within industrial clusters?

As one of this study's main aims, the DPP method's effect on the performance of the supply chain has been analysed. The results (path coefficient= 0.910 and T-value= 49.704, p-value=0) confirm that the DPP method positively impacts SC performance, and hypothesis H2 was supported. It means that the companies with a higher score in leagile strategy (DPP method) also have a higher score in supply chain performance (TSCV). ***The DPP method directly affects the supply chain performance in companies within industrial clusters***.

Is the relationship between SCs' drivers and DPP moderated by the Basis & Foundation factor of the industrial clusters?

This study collected data from the experts within companies and members of industrial clusters. Also, all the respondents are checked based on the panel selection and participants' profile questions in the questionnaire. The results have shown that Basis & Foundation factor directly impacts the relationship between SCs' drivers and DPP. It means that the Basis & Foundation factor has an impact, but the effect would be decreased by increasing the score of the SCs' drivers. In other words, the Basis & Foundation factor has a higher impact on the companies with the lower level of SCs' drivers. In addition, the moderating effect of the Basis & Foundation factor is higher on the relationship between location driver and DPP (t-value=3.435) than the inventory and DPP (t-value=3.002). Also, the results didn't support the moderating effect of the Basis & Foundation factor on the relationship between production driver and DPP (TV=1.396@ PV=0.163 in LLCI=-0.224, ULLCI=0.148) and sub-hypothesises H3-1 was not supported.

Is the relationship between SCs' drivers and DPP moderated by the market factor of the industrial clusters?

This study showed that the market factor negatively impacts the relationship between SCs' drivers and DPP. It means that the market factor has an effect, but the impact would be decreased by increasing the score of the SCs' drivers. In other words, the market factor has a higher impact on the companies with the lower level of SCs' drivers. In addition, the moderating effect of the market factor is higher on the relationship between inventory and DPP (T-value= 3.339) than information driver and DPP (T-value= 2.682). Also, the results didn't support the moderating effect of a market factor on the relationship between location driver

and DPP (TV= 1.832 @ PV= 0.067 in LLCI=-0.016, ULLCI=0.13) sub-hypothesises H4-2 was not supported.

Is the relationship between SCs' drivers and DPP moderated by the Business & Enterprise factor of the industrial clusters?

This study showed that the Business & Enterprise factor negatively impacts the relationship between SCs' drivers and DPP. It means that the Business & Enterprise factor has an impact, but the effect would be decreased by increasing the score of the SCs' drivers. In other words, the Business & Enterprise factor has a higher impact on the companies with the lower level of SCs' drivers. In addition, the moderating effect of the Business & Enterprise factor is higher on the relationship between inventory driver and DPP (T-value=3.475) than information and DPP (T-value=2.846). Also, the results didn't support the moderating effect of the Business & Enterprise factor on the relationship between location driver and DPP (LLCI=-0.245, ULLCI=0.065) due to its TV moderator variable (1.848 @ PV=0.071) was lower than the threshold limit. In addition, the results didn't support the moderating effect of the Business & Enterprise factor on the relationship between production and DPP (TV= 1.882 @ PV= 0.06 in LLCI=- 0.193, ULLCI=0.017); hence the sub-hypothesis H5-1 and H5-2 were not supported.

7.3 Theoretical Contribution – Moderating effect of industrial clusters factor

Many studies in the leagile SC literature examined the relationship between the different factors of SC and leagile SC. However, to my knowledge, none has analysed the industrial clusters forces impacting leagile implementation. One of the main theoretical contributions of this study was exploring the moderating effect of industrial clusters on the relationship between supply chain drivers and the DPP method. A long time has passed since the introduction of the leagile strategy. Many researchers have tried to identify the best and most effective ways to implement a leagile strategy. They always tried to analyse the impact of various factors (internal and external factors) on the success of implementing the leagile strategy within SCs.

Most of these scholars have examined the models presented in a case study and presented their results to develop leagile strategy theories. The researchers constantly review and compare their results with the results of previous works and provide solutions for developing leagile strategy due to the differences in the research method and nature of the case studies (such as environment, geographical location, and respondents to the questionnaire). Given the development of global supply chains and the intensification of competition between companies and their supply chains, a leagile strategy has been introduced as an effective strategy. It is

undeniable that the competition among companies and customers' expectations and needs levels have grown. In the past, a company that produced standard products could rely entirely on the lean principle. Likewise, companies with innovative products could depend on an agile method. But in today's business world, companies are under immense pressure and should respond to the customers' expectations and reduce costs to compete with their rivals. This study has theoretically contributed to leagile SC by introducing the Basis & Foundation, Market, and Business and Enterprise as three success factors of industrial clusters since they negatively moderate the relationship between SCs' drivers and DPP.

This study's second significant theoretical contribution is assessing the impact of each SC's driver (production, inventory, transportation, information sharing, and location) on the DPP. The success factors of industrial clusters and their measures were explored by reviewing the literature. Then, the constructs of the industrial clusters' factors were confirmed by conducting CFA. The moderating effect of the industrial clusters' factors (i.e., basis & foundation, market, and business & enterprise) on the relationship between SCs' driver and DPP. Other researchers could use the findings of this thesis to analyse the effect of industrial clusters on leagile implementation. Researchers in the leagile SC are advised to test the moderating effect of the 1) basis and foundation on the relationship between location, inventory, and information drivers and DPP 2) Market on the relationship between production, inventory, and information drivers and DPP 3) business & enterprise on the relationship between location and information drivers and DPP.

7.4 Empirical Contribution

Findings provided recommendations for SC managers, industrial clusters coordinators, and companies' directors to implement leagile strategy over their SC. Results confirmed that the leagile strategy could help companies increase their TSCV. In addition, companies within industrial clusters do not have obstacles to developing SC leagile strategy. In other words, although companies should strive to strengthen their position in their industrial cluster, industrial cluster membership was not recognised as a hindrance to implementing a leagile strategy. In addition, it was clarified that:

- By breaking the due date into short slots and reducing the amount of demand instead of a more extended due date, the company can reduce the inventory level and cost of the final products and respond faster and better to changes in customer demand needs.

- The company's interaction with other members of the industrial cluster and establishing reliable relationships can reduce production costs such as labour, equipment, and raw materials and improve operational efficiency. This way, companies can adopt the leagile strategy and improve SC performance by stimulating the production driver.
- The development of IT/ICT in the presence of reliability and commitment among the companies within the industrial cluster can effectively help companies implement the leagile strategy by creating new opportunities and rapid sharing of accurate and correct information.
- Access to foreign markets requires the development of information-sharing capabilities and adjusting to global industry standards. By facilitating the flow of information from foreign markets to the upstream members of the SCs, companies can manage work-in-progress inventory instead of customising the final product based on predetermined customer needs.
- The companies with low SC driver scores should aim to build their network within their industrial cluster. In this way, they can improve the effectiveness of the DPP method and further the SC performance.

7.5 Limitations and suitability

The generalisation of outcomes of this study is restricted to several facts and assumptions which must be considered. This thesis has developed and operationalised a conceptual model. In order to operationalise the model each construct was measured using manifest variables that can be utilised to estimate the role of SC factors on the TSCV. It would be beneficial to realise the other aspects of SC's supply chain uncertainties (such as energy and labour) in a future research construct. In addition, the studied variables and data deployed in the current construct were collected in a short time frame (1 year). As a cross-sectional study, the longer time of the study could provide valuable data and information regarding the changes concerning the variables in the model, and the associated concepts.

Furthermore, this study has discrepancies in business life cycles for the adopted companies. Also, the organisations are deployed different supply chain strategies according to their life cycle stage. The stage of the business life cycle is not considered and included in the research model, collected data, and developed construct.

Moreover, as explained in chapter five, the transportation variable is removed from the final construct during the CFA and SEM analyses due to the remaining two measures (indicators) in the factor, creating a negative degree of freedom. Hence, considering more measures (i.e., indicators or items) for the transportation variable in the initial questionnaire could create an accurate construct to provide a more robust outcome about the role of transportation in the SC.

Also, this study has certain limitations that need to be considered, which could serve as a valuable guideline for other researchers, academics, and industrial supply chain managers to conduct future research in this field of study.

- The region of the industrial clusters plays a significant role in the findings of this study; therefore, the findings and recommendations of this study cannot be generalised on a global level, and it is limited to the region where the investigation has taken place. The contributions of this study demonstrated the functionality of the developed conceptual framework. It would be exciting to see how the model would be operationalised in different parts of the world and observe how the moderating variables would impact the relationship between the SCDs and the DPP, particularly in countries where the supply chain clusters have been developed more extensively.
- The data collected for this study is from three heterogeneous supply chain clusters, which could have impacted the outcome of the study due to the differences in the opinion between the research participants; it would be interesting to observe how the result could be changed if data is collected from homogeneous supply chain clusters.
- Another limitation of this study is that all the factors and indicators were placed throughout the literature; identifying and integrating more factors/indicators in the construct would certainly increase the accuracy of the findings in future studies.
- This study has collected data from only 212 research participants due to the size of the companies involved in the industrial clusters. 88% of the companies that participated in this study were SMEs, and about 12% are large enterprises; thus, the sample size of this study is relatively small. The analysis outcome could become more accurate by collecting a more extensive data set.

7.6 Recommendations for Future Research

As the first research that analyses the leagile strategy implementation by the DPP method in companies within the industrial clusters, this research only focused on the overall impact of the industrial clusters. Future research could consider the nature of industrial clusters as a factor and its effect on the relationship between the SC drivers and DPP. Indeed, the results might be different when analysing the proposed model with furniture or fish industrial clusters individually due to the nature of the industrial clusters and their products. Also, the moderating effect of the industrial cluster could be analysed on the relationship between DPP and SC performance. It is worth considering how much companies can benefit from implementing a leagile strategy in the SC network within industrial clusters. Finally, the scholars can contribute to the literature by testing the proposed model to analyse the directions and intensity of the moderating variables over other industrial clusters.

7.7 Concluding remarks

This study analysed the relationship between SCs' drivers and DPP, DPP and SCs' performance. Furthermore, the survey was conducted in three industrial clusters to examine the moderating effect of the industrial clusters' factors between SCs' drivers and DPP (i.e., Basis and Foundation, Market, and Business and Enterprise). To this end, the literature has been reviewed, and a model is presented with five hypothesises and 25 sub-hypothesises. Data have been collected from 212 respondents who were experts in SC's strategies and industrial clusters within their companies. This study examines the effect of SC drivers on implementing the leagile strategy and the influence of DPP on the performance of the SC quantitatively. The results confirmed that the SC drivers include information sharing, production, location, and transportation, which significantly and positively impact adopting the leagile strategy in SCs. Also, the SC performance in terms of cost, quality, service, and lead-time has been considerably influenced by the leagile approach. Therefore, the companies could adopt a leagile strategy more effectively with an enhanced level of their SCs drivers and subsequently improve the performance of their SC.

Most previous works on leagile have studied companies' relationships only under the SC network. There has been a conspicuous lack of results on leagile implementation in companies with connections within an industrial cluster and the SC network. So, this study analyses the effect of industrial clusters factors on the leagile strategy implementation. Three factors, Basis and Foundations, Market, and Business and Enterprise, have been explored by reviewing the

literature to analyse the industrial cluster's moderating (indirect) effect on the relationship between SC drivers and DPP.

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Appendices

9.1 Appendix 1: Functional Versus Innovative Products: Differences in Demand

Functional Versus Innovative Products: Differences in Demand

	Functional (Predictable Demand)	**Innovative** (Unpredictable Demand)
Aspects of Demand		
Product life cycle	more than 2 years	3 months to 1 year
Contribution margin*	5% to 20%	20% to 60%
Product variety	low (10 to 20 variants per category)	high (often millions of variants per category)
Average margin of error in the forecast at the time production is committed	10%	40% to 100%
Average stockout rate	1% to 2%	10% to 40%
Average forced end-of-season markdown as percentage of full price	0%	10% to 25%
Lead time required for made-to-order products	6 months to 1 year	1 day to 2 weeks

* The contribution margin equals price minus variable cost divided by price and is expressed as a percentage.

Figure A1: Functional versus innovative products: differences in demand (adopted from Fisher 1997).

9.2 Appendix 2: Supply Chain Structure and Decoupling point

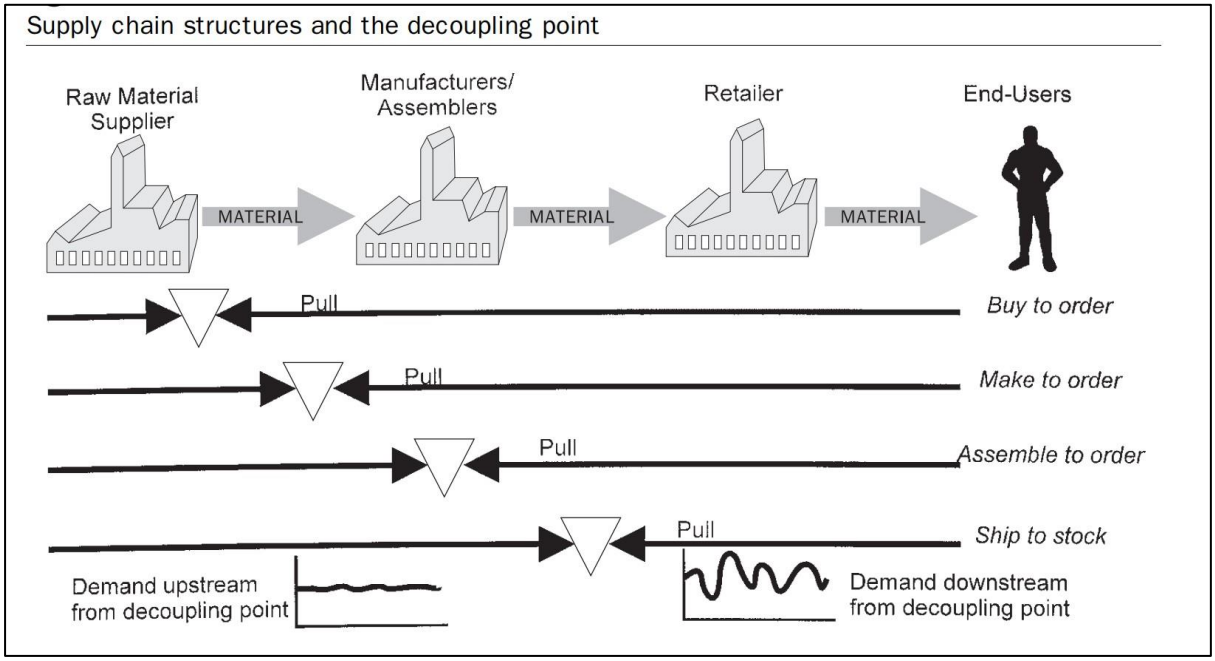

Figure A2: supply chain structure and decoupling point, (adopted from Hoekstra, and Romme, 1992).

9.3 Appendix 3: Hybrid Strategies

Hybrid strategies	Appropriate market conditions and operating environment
Pareto/80:20 Using lean methods for the volume lines, agile methods for the slow movers.	High levels of variety; demand is non-proportionate across the range.
De-coupling point The aim is to be lean up to the de-coupling point and agile beyond it.	Possibility of modular production or intermediate inventory; delayed final configuration or distribution.
Surge/base demand separation Managing the forecastable element of demand using lean principles; using agile principles for the less predictable element.	Where base level of demand can confidently be predicted from past experience and where local manufacturing, small batch capacity is available.

Figure A3: Hybrid Strategies (Adopted from Christopher and Towill 2000).

9.4 Appendix 4: A conceptual framework of leagility index

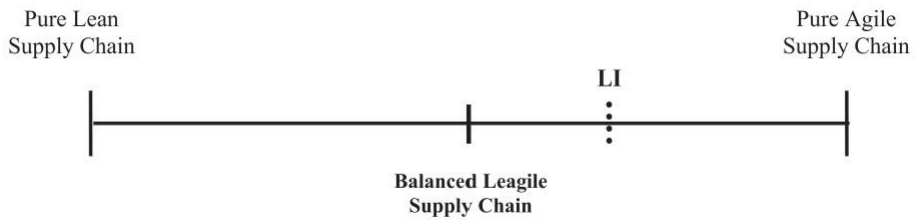

Figure A4: A conceptual framework of leagility index (LI) (Adopted from Fadaki et al. 2019a)

9.5 Appendix 5: Questionnaire and Invitation form

Questionnaire

INVITATION TO PARTICIPATE IN A RESEARCH PROJECT

A) PARTICIPANT INFORMATION

Project Title: A Study of Hybrid Leagile Supply Chain Strategy on the performance of the Industrial Clusters in Mazandaran Province

Investigators:

Name: Soheil Zargham Khoei

Email: **szargham@bournemouth.ac.uk**

Name: Sid Ghosh

Email: **sghosh@bournemouth.ac.uk**

Dear Participant

You are invited to join in research conducted by Bournemouth University. Please read this questionnaire and be confident that you realize it before deciding whether to complete the form. If you have any questions, please contact one of the investigators. This research is done as part of the requirements of a PhD candidature. We select you as an expert in supply chain management within the industrial cluster (i.e., furniture, agriculture machinery and equipment, and trout fish) in Mazandaran providence, Iran.

Research highlights

In a competitive market with unexpected fluctuations and deep uncertainty, industrial clusters are forced to implement appropriate strategies for gaining a competitive advantage. Several supply chain strategies such as lean, agile, and hybrid (leagile) were developed to improve the performance of the companies in supply chains. The main goal of the lean strategy is to improve profits by reducing cost, which is primarily concerned with eliminating waste to maximise profit. The agile concept is about flexibility and rapid response to demand variation in a changing market environment. Leagile strategy combines both strategies that benefit lean and agile methods.

This study evaluated the trade-offs of leanness and agility on five supply chain drivers: production, location, inventory, transportation, and information. In this regard, Decoupling Point Position (DPP) index is employed to evaluate the performance of supply chain strategies in industrial clusters. Total Supply Chain Value (TSCV) in terms of cost, quality, service, and lead-time would be deployed to analyse the performance of the supply chain.

Furthermore, the direct and indirect impact of the industrial clusters' factors, including basis and foundation, business and enterprise, and market factors, would be analysed as Moderating variables. Therefore, this research studies the relationships between the DPP index, supply chain drivers, industrial clusters factors, and supply chain performance.

The developed framework was applied to test the hypotheses' validity using survey data from senior experts and executive management in three industrial clusters, including furniture, agricultural machinery and equipment, and trout fish in Mazandaran province. A model is developed to explore the impact of supply chain drivers on the DPP and indicate the DPP's effect on the supply chain's performance in terms of TSCV.

Participation Procedure

Your contribution is voluntary. You are free to withdraw this request. The current questionnaire consists of 8 questions about your profile and 68 main questions. Almost 30 minutes are required to complete the form. There is one type of question in the current questionnaire. The scale includes six options from 'Strongly Disagree' to 'Strongly Agree.' Please select one option.

Risks and Benefits

There are no risks or benefits involved in this research.

Confidentiality and Anonymity

All information provided by you will be treated with full confidentiality.

Participant Rights

The right to withdraw from participation at any time.

The right to have any questions answered at any time

Yours sincerely

Soheil Zargham Khoei

9.6 Appendix 7: Panel Selection

Did you have any specific role in configuring your company's industrial cluster?

- Yes
- No

Do you have any specific role in coordination with upstream and/or downstream side of your supply chain in industrial cluster?

- Yes
- No

Participants' profile

PP1. Position in the company

- Managing Director (1)
- Supply Chain Manager (2)
- Operations Manager (3)
- Procurement/Purchasing Manager (4)
- Inventory Manager (5)
- Retail and Marketing Managers (6)
- Distribution Manager (8)
- Other (9) ……

PP2. Education

- Bachelor and below (1)
- Master (2)
- PhD & Above (3)

PP3. Work Experience

- <5 Years (1)
- 5–9 Years (2)
- 10–20 Years (3)
- >20 Years (4)

PP4. Work Experience in the industrial cluster

- <5 Years (1)
- 5–9 Years (2)
- 10–20 Years (3)
- >20 Years (4)

PP5. Industrial clusters

- Wood and furniture products (1)
- Agricultural machinery and equipment (2)
- Trout fish (3)

PP6. Industry

- Food product (1)
- Wood and fibreboard (2)
- Metal (3)
- Textile (4)
- Chemical (5)
- Machinery and equipment (6)
- Retail and marketing (7)
- Other (8) ……

PP7. Number of employees within the company

- <30 (1)
- 30-60 (2)
- 60-100 (3)
- >100 (4)

PP8. Years Since the company joint the industrial cluster

- < 3 years (1)
- 3-8 Years (2)
- >8 Years (3)

Main questions - Decoupling Point Position

DPP1. The main production approach of the company is designed to respond to all market needs.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

DPP2. The main production approach of the company is designed by considering the maximum efficiency to decrease the costs.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

DPP3. The main inventory management of the company focuses on holding work in process products rather than the final product.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

DPP4. The main inventory management of the company focuses on holding final products rather than work in process product.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

DPP5. In the company's supply chain distribution policy focuses on distributing products according to the markets demand.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)

- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

DPP6.In the company's supply chain distribution policy focuses on distributing products to the market after receiving the actual demand from market.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)
- Strongly Agree (5)

DPP7. In the company's supply chain, information shares from downstream to upstream and vice versa.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

DPP8. The company only shares information with limited partners in the industrial cluster.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Production factor

Pro1 Products due-date is short in the company

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Pro2 The product cycle time is short in the company

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Pro3 The production variation cost in the company is high

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Pro4

Demand of products are high in the company

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Pro5 The production utilization rate is high in the company

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Pro6 The company's products design to have maximum performance and minimum cost.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)

- Agree (4)
- Strongly Agree (5)

Pro7 The company reduces any kind of waste as much as possible

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Inventory factor

INV1 High volume of raw materials holds in the company.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

INV2 Low volume of final products holds in the company.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

INV3 The demand is rather constant for final products in the company

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

INV4 The order point is rather fixed in the company

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

INV5 The inventory holding cost of the Final products is high in the company

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

INV6 Inventory turnover is high in the company

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Location factor

Loc1 The appropriate location of the company led to decrease company's cost includin land, energy, transport infrastructure, business services, telecommunications, and labou

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Loc2 There is appropriate infrastructure in terms of land, energy, transport, and telecommunications due to the location of the company

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Loc3 The suitable location of the company has enhanced your access to business services such as air, sea, and land transport services, financial services, legal services, and information technology.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Loc4 The suitable location of the company increases the availability and quality of labour education and skill.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Loc5 The company's location within the industrial cluster provides stability of government and tax policies.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Information factor

Inf1 The company shares enough and accurate information with its partners within the industrial cluster to respond to customers' changing needs.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Inf2 The company builds a partnership with a few partners within the industrial cluster to share enough and accurate information in order to reduce supplier uncertainty.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Inf3 The development of IT provides numerous opportunities for the company to increase the level of information sharing within the industrial cluster.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Inf4 Rapid development of IT technology forces the company to share more and accurate information with partners in the industrial cluster

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Inf5 Top management/coordinator of the industrial cluster supports the company in share information with other partners through supply chain.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Inf6 Top management of the company supports the company to share information.

- Strongly Disagree (0)

- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Inf7, IT enables the company to open up new opportunities for increasing value through information sharing within the supply chain.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Inf8 Trust among the partners within the industrial cluster has removed obstacles to information sharing between partners.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Inf9 Partner's commitment within the industrial cluster leads the company to share accurate information, which indicates a high level of information sharing.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Transportation factor

Loc1 Products and raw materials are delivered very fast among partners of the company within industrial cluster.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)

- Agree (4)
- Strongly Agree (5)

Loc2 The company's transportation system fulfil promises to consignees

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Loc3 Transportation proficiency improve the rate of utilization of facilities/equipment/manpower in providing the services of the company

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Industrial clusters basis and foundation

Bas1 There are skilful employees working in the company

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Bas2 The company has a high net working capital (financial resources)

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Bas3 The company engages in securing growth and revenue from industry sectors characterized by new and rapidly changing technology.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Bas4 The company considers technological innovation and R&D for improving its innovation Capacity.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Bas5 The company has great communication infrastructure for communicating with other companies in the industrial cluster.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Bas6 The company has a great deal of control over its external environment.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Bas7 The company has great deal of control over its internal environment

- Strongly Disagree (0)
- Disagree (1)

- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Bas8 The company has effective training and development policy

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Bas9 The company has high degree of work specialization

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Bas10 Rules and regulations of the company occupy a first place in the organizational structure.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Industrial clusters business and enterprise

Bus1 There are strong suppliers within the company's industrial cluster

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Bus2 There is strong cooperation among the companies in the industrial cluster.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Bus3 There are reliable companies within the industrial cluster

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Bus4 There are honest companies within the industrial cluster

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Bus5 Companies cooperate within the industrial cluster.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Bus6 There are strong competitors within the industrial cluster.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)

- Strongly Agree (5)

Bus7 All members have compiled rules of the industrial cluster.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Bus8 All members align with the goals of the industrial cluster.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Industrial clusters market

Mark1 The Company following constant sale policies within the industrial cluster.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Mark2 The demand of the company's products is high for local markets.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Mark3 The Company has positive outlook to the future of local markets.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Mark4The company connects to the local value chain of its products.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Mark5Distance of the company to foreign markets is short.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Mark6The company has positive outlook to the future of global markets.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Mark7There are no obstacles and limitations to foreign markets for the company within the industrial cluster.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Mark8The demand of the foreign markets' is high for the company.

- Strongly Disagree (0)
- Disagree (1)
- More or less Disagree (2)
- More or less Agree (3)
- Agree (4)
- Strongly Agree (5)

Total Supply Chain Value

TSCV1 How well does the company perform relative to its competitors in terms of cost?

- Much Worse (0)
- Worse (1)
- Somewhat Worse (2)
- Somewhat better (3)
- Better (4)
- Much Better (5)

TSCV2 How well does the company perform relative to its competitors in terms of quality?

- Much Worse (0)
- Worse (1)
- Somewhat Worse (2)
- Somewhat better (3)
- Better (4)
- Much Better (5)

TSCV3 How well does the company perform relative to its competitors in terms of lead-time?

- Much Worse (0)
- Worse (1)
- Somewhat Worse (2)
- Somewhat better (3)
- Better (4)
- Much Better (5)

TSCV4 How well does the company perform relative to its competitors in terms of service?

- Much Worse (0)
- Worse (1)

- Somewhat Worse (2)
- Somewhat better (3)
- Better (4)
- Much Better (5)

9.7 Appendix 6: Ethics Approval Notice

Ethics ID	Project Name	Risk	Status	Checklist	Feedback	View/Edit	Delete	Amendment
27667	Development of a Connectivity Map for Measurement of Total Supply Chain Value	High	Approved					