**Direct and Mediation Effect of Supply Chain Complexity Drivers on Supply Chain Performance: An Empirical Evidence of Organizational Complexity Theory**

**Abstract:**

**Purpose:** In today's globalized business environment, growing supply chain complexity (SCC) is arguably a major threat to the firm's business continuity with an adverse impact on the firm's competitive advantage and business performance. Researchers, though, investigated the impact of SCC drivers on a firm's operational performance, but the key question "Which supply chain complexity drivers severely impact the supply chain performance (SCP)?" remains largely unanswered from empirical research. The present study decomposes the SCC into four major constituting sub-categories (upstream, operational, downstream, and external) to explore the causal impact of SCC drivers on SCP in direct and mediated manner.

**Design/methodology/approach:** The indicators applied for measuring constructs in the 'Measurement model' are obtained from existing literature to increase the validity and reliability of the model. First, a pilot survey involving 25 SC managers from various manufacturing firms was conducted for indicator refinement and content validation. Second, the large-scale response data was collected through extensive surveys. This research explores the causality by testing the hypothesis applying Structural Equation Modelling (SEM) based on the responses received from 246 firms.

**Findings:** The study investigates the impact of SCC drivers on SCP through direct and mediation effect. The results indicate that upstream and operational SCC drivers play a mediating role in managing SCP. The findings reveal that upstream and operational SCC drivers adversely impact the SCP. Further, the impact of downstream complexity on SCP is moderated through operational complexity drivers. The result explains the theoretical relation among SCC drivers supported by empirical validity.

**Practical implication:** The outcome offers practical relevance to SC managers in SCC and SCP management. Knowing the effect of SCC drivers among themselves and on SCP will facilitate the SC managers in devising the right strategies. Our study provides a framework for prioritizing the resource in addressing the SCC issues among many.

**Originality/value:** The study addresses the apparent gap in the literature by modeling the impact of SCC drivers on SCP, which remained largely unexplored. First, it contributes to developing complex relationships among SCC drivers. Second, the direct and mediated causal effect of the SCC drivers individually and combinedly on SCP are explicated.

***Keywords:*** Supply chain complexity, supply chain management, supply chain performance, empirical research, Structural equation modelling.

**1. Introduction**

"Complexity is destroying profitability in many companies, and companies must reduce complexity if they are to survive and be profitable in a sustainable fashion" (Gilmore, 2008). The statement from the former executive vice president of global supply chain operations for Open Energy Corporation underscores the growing concern of the supply chain complexity (SCC) in causing uncertainty. Supply chains are becoming complex due to market uncertainty, shortening product life cycle, the rapid pace of new technological development, global geopolitical risk, growing customization (Wiengarten et al., 2017; Chand et al., 2017). Supply chain performance carries strategic significance as it is responsible for organizational performance (Whitten *et al*., 2012). In past studies, researchers investigated the negative impact of SCC on a firm's operational performance (Heim *et al*., 2014), delivery performance (Vachon and Klassen, 2002), manufacturing plant performance (Bozarth *et al*., 2009). Contrastingly, the adverse effect of SCC on performance is challenged by several researchers. It is argued that SCC might offer strategic competitiveness to a firm's business objective (Aitken *et al*., 2016) innovation management (Sharma *et al*., 2020), while internal complexity might not affect financial performance (Wiengarten *et al*., 2017). Menezes *et al*. (2021) presented a two-sided balanced argument of structural complexity on performance. While the positive impact of complexity during the initial development phase is evident, complexity erodes efficiencies beyond a considerable extent. Extant literature seems to be equivocal in acknowledging SCC as dysfunctional or strategic. However, the critical question "Why and how supply chain complexity impacts the supply chain performance in the presence of complex interactions?" remains largely unanswered from empirical research studies (Ateş *et al*., 2022).

Though existing literature highlighted the contextual importance of SCC and performance, a large part of the approach lacks comprehensiveness in capturing key SCC dimensions (Ateş *et al*., 2022). In the meta-analysis of SCC, Ateş *et al*. (2022) divide complexity in upstream, downstream, internal, and detail and dynamic; link it to several performance criteria. While their findings offer nuanced understanding, they leave the following critical research gap unexplored. Existing research seems insufficient to explain the interaction effect (‘why and how’) among SCC drivers and/or how they affect SCP in a complex interacted system. In one of the leading attempts, Dittfeld *et al*. (2018) investigated the interaction between types and levels of SCC. However, the conceptualization of their study is limited to the individual interaction of SCC. While qualitative and/or case study-based examination provides a reasonable understanding of interaction, it still lacks statistical generalization in quantifying the effect (Aitken *et al*., 2016). While the prior empirical studies give directionality of interaction, they are limited in quantifying the interaction among SCC drivers (Dittfeld *et al*., 2018). Lack of study on computing the magnitude of relationship limits the understanding of ‘how much firms can improve performance by reducing the supply chain complexity (Menezes *et al*., 2021).

The present work intends to answer several limitations described above, yet unanswered in empirical research. The contribution of this research is four-fold. First, it contributes to developing complex intervening relationships among SCC drivers in the presence of *‘simultaneous interactions’* (i.e., conceptualizing SCC as a connected network). Second, we explore the direct and mediated effect of the SCC drivers individually and combinedly on supply chain performance. While the extant literature primarily focuses on interaction within SCC drivers, this study aims to extend the interaction effect of SCC drivers on SCP. Thus, we intend to offer an enhanced understanding of SCC and its impact on SCP by unpacking the complex interaction. Third, apart from examining the interaction, our work proposes statistical validation of the findings with quantitative assessment. By estimating the magnitude of the relationship between the SCC and SCP, the results can guide supply chain practitioners in improving performance. Fourth, this study seeks to expand the ongoing discourse of SCC for the context of the manufacturing industry, as interactions among SCC can be context-specific (Dittfeld *et al*., 2018).

Knowing the directionality of relation with the significance level can help SC managers devise a strategy to manage and control SCC, thereby resulting in the desired SCP outcome. The research outcome aims to enrich SC practitioners with the necessary theoretical framework as a basis for decision-making. We hypothesize the relationships among the decision variables in coherence with existing literature to achieve this. This research proposed the theoretical model interlinking the afore-mentioned drivers of SCC with SCP to investigate the complex relation founded on academic research (Heim et al., 2014; Vachon and Klassen, 2002; Bozarth et al., 2009) and tested the model based on the collected data from supply chain managers of 246 manufacturing firms. Further, the inter-relationship among the SCC drivers is investigated, and the combined impact of SCC drivers on SCP was explicated.

In earlier studies, to measure SCC, researchers applied reflective scale (Bozarth et al., 2009) and numeric scale (Bode et al., 2015), among others. Wiengarten *et al*. (2017) emphasized the need for a greater inclusive representation of complexity constructs. This study conceptualizes the SCC and SCP constructs on a formative scale using measurement indicators of SCC drivers for three reasons. Firstly, unlike the reflective scale, the direction of causality is from measurement indicators to the SCC drivers. Second, indicators become non-interchangeable among themselves as they measure distinctly different dimensions of SCC drivers, and lack of covariance among measurement indicators (change in one measuring indicator is not necessarily related to other indicators) (Jarvis et al., 2003). Justifiably, we apply the formative measurement model in structuring the research design. Hence, constructs in this research are being formed, caused, and altered by its measurement indicators. This approach adds methodological uniqueness for measuring SCC and SCP and complements existing research with theoretical novelty.

The research work presented in this paper is organized in the following manner. The theoretical relationship of various SCC drivers with SCP through the literature review and proposed the research framework by constructing the hypothesis in Section 2. The complete methodology followed in conducting this research is covered in Section 3. While Section 4 explains the outcome of the data analysis in the results section, the paper's contribution is summarized in Section 5. Section 6 finishes the present work by mentioning several broad research areas for future exploration.

**2. Literature review**

**2.1 Theoretical framework for analysing SCC & SCP**

SCC is integral due to the detail and dynamic drivers of complexity. The 'detail' complexity is caused by interaction among multiple nodal agencies present in the network, numerous interconnected relations, and the complex structure of the supply chain with multiple sub-systems (Bozarth *et al*., 2009). The 'dynamic' complexity results from uncertainty and external conditionality (Serdarasan, 2013; Isik, 2010). Therefore, it is inferred that the increase in mutually interacting factors/drivers present in a system is responsible for causing a higher level of complicatedness in the 'structure' and 'behaviour' of the plan (Lu and Shang, 2017). SCC is likely to exhibit an increased variety of behaviours in an organisational context due to multiple interconnections among nodes (Manuj and Sahin, 2011).

Bozarth *et al*. (2009) classified SCC drivers as detail and dynamic complexity covering the scope of manufacturing plants in three significant areas upstream, internal manufacturing, and downstream drivers. Further, Manuj and Sahin (2011) emphasized the importance of SCC management by integrating the firm's upstream and downstream channel partners. According to them, the inclusion of intra and inter-organizational factors is critical for effective decision-making. Extending the understanding, Aitken *et al*. (2016) summarized the literature of SCC with drivers as internal (with firms' operation), external (suppliers and customers), and environmental based on origination point. While the 'detail' aspect in each aforesaid category tends to capture the variety/numerousness, the 'dynamic' aspect focuses on the uncertainty/unpredictability of internal and external factors. Notably, the focal firm can primarily manage detail and dynamic complexity management in the categories (upstream, internal, downstream). However, external/environmental dynamic complexity drivers typically fall beyond the firm's control boundary and seem to impact other drivers (Serdarasan, 2013). Expanding the prior studies, Kavilal *et al*. (2017) categorized the SCC drivers into four major clusters: supply base (upstream), internal, customer base (downstream), and added external complexity (beyond the control of the focal firm and driven by external environmental changes). Similarly, dynamic factors like geopolitical trade relations, technological trends, product lifecycle, market uncertainties are assigned in the category of external environmental (Dittfeld *et al*., 2018; Serdarasan 2013). In the latest comprehensive review on SCC, Ateş *et al*. (2022) divided complexity in upstream, downstream, internal, and detail and dynamic; linked it to several performance criteria. Two final remarks. First, in line with prior literature, we conceptualize SCC drivers as upstream (supplier side), operational (internal manufacturing related), downstream (customer-side), and external (beyond the control of the organization and driven by external environment). Second, detail and dynamic attributes are incorporated by structuring the SCC constructs with formative indicators representing the SCC. We will explain these SCC drivers in greater detail in the following sections. The entire supply chain complexity model is pictorially presented in Figure 1.

Several prior studies highlighted the relational impact of SCC on SCP. Bozarth *et al*. (2009) analysed the adverse effects of three measures of SCC (upstream, internal, and downstream) on plant performance. Along similar lines, others investigated the negative impact of SCC on a firm's operational performance (Heim *et al*., 2014) delivery performance (Vachon and Klassen, 2002). Challenging the earlier view of SCC on SCP, a number of studies advocated the positive effect of accommodating SCC in improving performance. Aitken *et al*. (2016) argued the SCC to be 'necessary' if it fits in organisational 'strategy' and supports the business performance. Further, SCC might offer a competitive advantage in firms' innovation performance (Sharma *et al*., 2020). Echoing similar findings, Ateş *et al*. (2022) suggested a favourable impact of SCC on innovation and financial performance. To that end, complexity limited to a certain extent is necessary to differentiate a firm (Wiengarten *et al*., 2017). Rather than taking any distinctive pole position, some researchers suggest a balanced dynamic approach in managing SCC and performance. Dittfeld *et al*. (2018) expanded the complexity paradigm by investigating the individual interaction between the types and levels of SCC for the food industry. According to them, SCC and performance management might be specific to industry and context without being generic. Evidently, the existing body of literature exploring the effect of SCC on SCP seems divergent, to some extent debatable, and thereby lacks generalisation. However, it captures the importance of SCC and SCP but lacks inclusiveness in studying key SCC dimensions (Ateş *et al*., 2022). The extant study on SCC interactions is grossly based on case studies and may be considered directional at large. Thus, we recognise the timely need for statistical validation of SCC interactions with a sufficiently large sample size before generalisation (Aitken *et al*., 2016).

External SCC

Upstream SCC

Operational SCC

Downstream SCC

Customers

Tier n

Tier 1

Dealers

**Figure 1:** Supply chain complexity model-Conceptualized

*2.1.1 USCC with drivers*

USCC is commonly referred to as 'detail and dynamic complexity' originating at the supply base being managed by a focal firm (Bozarth *et al*., 2009). The three significant drivers for USCC are the number of suppliers directly handled by the nodal firm (horizontal complexity), the number of tiers of suppliers (vertical complexity), and the geographical distribution of the supplier base (spatial complexity) (Sharma *et al*., 2020). Horizontal complexity is usually defined as the "width" of the supplier base. The presence of information and knowledge asymmetry in vertical and spatial complexity is likely to impact buyer-supplier collaboration efforts with an outreaching impact on supply chain performance (Lu and Shang, 2017). Additionally, spatial complexity (geographically dispersed supply chain network) entails an extended network for material flow, usually associated with longer lead time, multi-modal transportation, increased logistical touchpoints (Bode and Wagner, 2015). Thus, to reduce USCC, managing the integration with supply chain partners is important for the focal firm in allaying concerns emanated from global supply chain complexity (Gunasekaran *et al*., 2014). The three aspects of USCC explains near independent dimensions of USCC and are unlikely to represent any meaningful commonality. Measurement indicators of USCC are not interchangeable amongst each other as indicators measure different dimensions of USCC. A change in one measuring indicator is not necessarily related to other indicators. For example, the number of tiers of suppliers is not associated with the geographical spread of the suppliers. Likewise, the total number of suppliers handled by a focal firm is seldom related to the spatial distribution of suppliers. Therefore, it can be argued that all three drivers of USCC (horizontal complexity, vertical complexity, and spatial complexity) are individually and cumulatively forms the USCC. Hence, we propose that these three drivers are formative due to their causal direction in aggregating the construct USCC (ref: Table 1).

*2.1.2 OSCC with drivers*

OSCC is often called internal manufacturing complexity, which explains the 'level of detail and dynamic complexity found within the manufacturing facility's products, processes, and planning and control systems' (Bozarth *et al*., 2009). This complexity is primarily driven by part complexity (variety and numerousness of parts), product complexity (number/variety of products), process complexity, and complexity in managing the product life cycle (Menezes *et al*., 2021; Closs and Nyaga, 2010; Kavilal *et al*., 2017). Due to product diversity, sourcing more unique parts usually requires individual supply chains for schedule attainment. Therefore, an increase in exclusive part complexity often results in a commensurate rise in supply chain complexity with an increased risk of disruption (Inman and Blumenfeld, 2014). Enhanced product diversity marks the upsurge in the number of nodal transactions in the supply chain with an associated cost of managing complexity in the entire series of activities (Jacobs and Swink, 2011). Hence, product complexity is credited as the most influencing factor in supply chain strategy (Paulonis and Norton, 2008). Increasing customization to match customer expectations on product variety often drives part and product complexity for the manufacturers (Gunasekaran et a., 2014). Product complexity (variety and numerousness) often results in increasing manufacturing lead time, the higher number of platform changeovers, greater resource involvement to manage operations (Bozarth et a., 2009). Process complexity is “generated due to various operational and logistical processes due to a lack of standardization” (Kavilal *et al*., 2017). An increase in product life-cycle complexity might generate operational complexity in two ways, first is the increase in variation of components and the second-greater need for system adjustment (Bozarth *et al*., 2009). The indicators have a relatively little overlap in representing the OSCC. Ex: The antecedents of part variety and complexity, product complexity, process complexity, and product life-cycle complexity are reasonably unrelated. To elaborate, ‘part complexity’ is often represented by the variety and numerousness of components handled by the entire supply chain. According to MacDuffie *et al*. (1996), managing part complexity by nature can fundamentally impact firms’ operations and be peripheral to its upstream supply chain partners. According to their findings, part complexity indexed by the variables such as higher number of suppliers increased number of parts have no meaningful contribution to process complexity. However, when measured by ‘percentage of common parts across operations, part complexity may impact the process. Firms as an organizational strategy might be prepared to absorb part complexity (variety and numerousness) to a certain extent to improve customization without any considerable impact on its processes. Early engagement with supply chain partners in product development deep supplier relationships in product innovation might help firms overcome part complexity (Liker and Choi, 2004). Therefore, conceptually, an indicator measuring a part complexity may not correlate with an indicator measuring process complexity. OSCC is caused singularly or cumulatively by afore-discussed four drivers, part complexity (OSCC1), product complexity (OSCC2), process complexity (OSCC3), and managing product lifecycle complexity (OSCC4) (Vickery *et al*., 2016). Therefore, OSCC is posited as a formative construct represented by these four indicators (OSCC1 to OSCC4) aggregately in Table 1.

*2.1.3 Downstream supply chain complexity (DSCC) with drivers*

DSCC is usually described as 'customer base complexity', explained 'as the level of detail and dynamic complexity originating in a manufacturing facility's downstream markets' (Bozarth *et al*., 2009). Complexity drivers arguably play a key role in causing DSCC as generated by a) the number of customer orders (DSCC1), b) the number of associated varieties of customer-specific product requirements (DCSS2), c) demand variability from customers (DSCC3) (Gerschberger and Hohensinn, 2013). The indicators DSCC1, DSCC2, and DSCC3 explain a variety of customer-specific differentiation and variability of demand, respectively. These indicators explain different aspects of DSCC and rarely represent each other. Measures for analysing DSCC1, DSCC2, and DSCC3 are seemingly unrelated to each other. DSCC tends to increase with the increase in customer base associated with in-build heterogeneity of product requirements added by the change in customer demand (Vollmann *et al*., 2005). Hence, these factors (DSCC1, DSCC2, and DSCC3) are attributed individually/cumulatively in causing DSCC in Table 1.

*2.1.4 External supply chain complexity (ESCC) with drivers*

ESCC is described as the complexity generated from sources beyond the firms' scope of supply chain and thereby have limited control over them (Ateş *et al*., 2022). Two important drivers that play a significant role in this are uncertainty in the market, usually due to the multiplicity of factors (summarized in Table 1), and technological disruption (development of new technologies, products, processes, new materials, etc.) (Kavilal *et al*., 2017). Supply chain uncertainty due to globalized business factors (ESCC1) and technological disruption (ESCC2) due to the emergence of new technologies are two separate indicators that cannot represent each other in a meaningful way. Indicators applied to measure uncertainty in the market (ESCC1) need not be associated with indicators quantifying technological disruption (ESCC2). Hence, we have applied these two drivers in measuring the ESCC as a formative construct (please ref Table 1).

**2.2 Supply chain performance (SCP)**

SCP is commonly explained as a systematic process of measuring the effectiveness and efficiency of supply chain operations (Anand and Grover 2015). It is also a measure of a firm's supply chain capability to deliver products and services to the customer with ‘proper quantity, and right quality’ as per committed time with an overall objective to minimize the total cost (Zhang and Okoroafo 2015). Supply chain performance is extensively dependent on the partnering organisations responsible for ‘agility, adaptability and alignment’ (Whitten *et al*., 2012). This emphasises the need for SCP metrics, grossly focussed on capturing the inter-organisational performance of the supply chain. In one of the pioneering investigations on measuring SCP, Beamon (1999) classified the SCP metrics in three broad categories, levelled as resources (associated SC cost), output (delivery and quality), and flexibility. Applying a process-based model, Chan and Qi (2003) categorised the SCP measures in three major segments, i.e. inputs (on-time delivery and cost), outputs (quality and flexibility), and composites (interfacial between input and output measures). Most of the SCP definitions focus on a combination of key qualitative and quantitative characteristics, such as-flexibility to meet end-customer demand, on-time delivery of goods and services, quality of goods and services delivered to the customer, and total cost of managing end-to-end supply chain (Cai *et al*., 2009; Maestrini *et al*., 2017). In alignment with prior studies, we have constructed SCP as a formative construct measured by four key dimensions as indicators of SCP, a) supply chain cost (SCP1), b) supply chain quality (SCP2), c) on-time delivery (SCP3), d) flexibility of the supply chain (SCP4) (please refer Table 1).

Supply chain cost (SCP1) is aggregately represented as resources, distribution, manufacturing, and inventory costs (Beamon, 1999). Following Pettersson and Segerstedt (2013), supply chain cost (SCP1) performance is measured using supply chain cost volume ratio (SCCR), which is explained as SCCR: (net sales-supply chain cost)/net sales. Over time, an increase in the SCCR value is considered beneficial, while a decrease in SCCR is unfavourable. Likewise, a firm's supply chain quality is measured as the percentage of accurately specified goods delivered to customers conforming to product and service quality as per customer requirement (SCP2) (Cai *et al*., 2009). Similarly, supply chain on-time delivery (SCP3) is usually measured as a percentage of orders delivered on or before the committed date by the firm (Beamon, 1999). Therefore, the increasing trend of this percentage is considered favourable as it indicates an increasing number of delivery commitments by the firm. The need for flexibility in the supply chain is construed as the agility and adaptability of supply chain participants (Whitten *et al*., 2012). The flexibility of the supply chain (SCP4) is measured as the ability of firms' supply chain to respond to the number and variety of product modifications without incurring any meaningful impact on performance outcome (Chan 2003).

**2.3 Formation of constructs**

This research has followed the four-point guidelines Jarvis *et al*. (2003) suggested in determining whether the construct is formative or reflective. The guidelines are a) direction of causality between indicator and construct, b) interchangeability of indicators representing a construct, c) covariation among the indicators, d) 'nomological network of indicators. We evaluated each construct based on the aforesaid four-point guidelines and assigned the type to the constructs for further evaluation. A detailed explanation in support of our construct formation and categorization is tabulated in Table 1.

**Table 1:** Summary of formative and reflective constructs with corresponding indicators

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Formative Constructs | Indicators | A. Direction of causality | B. Interchangeability of the indicators | C. Covariation among the indicators | D. Nomological validity of the construct/indicators |
| Upstream supply chain complexity (USCC) (Bode and Wagner, 2015; Bozarth et., 2009; Sharma *et al*., 2020; Gunasekaran *et al*., 2014; Lu and Shang, 2017) | Horizontal complexity (USCC1) | Indicator to construct USCC1🡪 USCC, USCC2🡪USCC,  USCC3🡪 USCC, USCC is represented collectively by horizontal (USCC1), vertical (USCC2) and spatial supply chain complexity (USCC3). | Measurement indicators of USCC are not interchangeable amongst each other as indicators measure different dimensions of USCC; | A change in one measuring indicator is not necessarily related to other indicators. For instance, number of tiers of suppliers are not associated with the geographical spread of the suppliers. Likewise, total number of suppliers handled by a focal firm is seldom related to the spatial distribution of suppliers. | Arguably, neither the indicators of USCC are affected by the same set of antecedents nor indicators lead to similar outcomes. The nomological validity of USCC can be established through the derived value of structural path co-efficient. |
| Vertical complexity (USCC2) |
| Spatial complexity (USCC3) |
| Operational supply chain complexity (OSCC) (Menezes *et al*., 2021; Closs and Nyaga, 2010; Kavilal *et al*., 2017; MacDuffie *et al*. (1996); Vickery *et al*., 2016; Bozarth et., 2009). | Complexity by number and variety of parts (OSCC1) | Indicator to construct OSCC1🡪 OSCC, OSCC2🡪 OSCC, OSCC3🡪 OSCC,  OSCC4🡪 OSCC, | The indicators are explaining different aspects of OSCC with a relatively insignificant overlap in representing the OSCC. | For instance, conceptually, an indicator measuring part variety complexity will not have to correlate with an indicator measuring process complexity. | The nomological validity of the OSCC construct can be signified by assessing the structural path connecting it with causing construct (OSCC) and consequential constructs (SCP). |
| Complexity due to the number and variety of products (OSCC2) |
| Complexity related to processes (OSCC3) |
| Complexity in managing product life cycle (OSCC4) |
| Downstream supply chain complexity (DSCC) (Gerschberger and Hohensinn, 2013, Bozarth *et al*., 2009; Vollmann *et al*., 2005) | Number of customers (DSCC1) | Indicator to construct DSCC1🡪 DSCC,  DSCC2🡪 DSCC,  DSCC3🡪 DSCC, The DSCC1, DSCC2 and DSCC3 indicators play a major role in causing the DSCC. | The indicators DSCC1, DSCC2 and DSCC3 are explaining the number of customers, variety of customer-specific product requirement and variability of demand, respectively. These indicators are conceptually explaining seemingly unconnected aspects of DSCC and cannot represent each other. | Measures for analysing several customers (DSCC1), customized product requirement (DSCC2) and demand variability of customers (DSCC3) are seemingly unrelated to each other. | By analysing the structural path connecting it with affecting constructs (SCP). |
| This complexity caused by a variety of customer-specific product requirements (DSCC2) |
| Demand variability (DSCC3) |
| External supply chain complexity (ESCC) (Ateş *et al*., 2022; Kavilal *et al*., 2017) | Uncertainty in the market (ESCC1): Supply chains are vulnerable to change in rules and regulations of the country, region of its operation. Market uncertainty caused due to globalized economic disruption, currency exchange fluctuations, cyclicity of market, geo-political events increase complexity significantly. | Indicator to construct ESCC1🡪 ESCC,  ESCC2🡪 ESCC, | Supply chain uncertainty due to globalized business factors (ESCC1) and technological disruption (ESCC2) due to the emergence of new technologies are two separate indicators that cannot represent each other in a meaningful way. | Indicators applied to measure uncertainty in the market (ESCC1) need not to be associated with indicators quantifying technological disruption (ESCC2). | Nomological validity of ESCC construct can be checked by assessing the path coefficient with consequential constructs (SCP). |
| Technological disruption (ESCC2): continuous changes in technological innovation and disruption forces the firm to evolve with new products, processes, materials, supply chain partners. |
| Supply chain performance (SCP); (Anand and Grover 2015; Whitten *et al*., 2012; Zhang and Okoroafo 2015; Beamon 1999; Cai *et al*., 2009; Maestrini *et al*., 2017) | Cost for all supply chain processes (SCP1) | Indicator to construct SCP1🡪 SCP, SCP2🡪 SCP, SCP3🡪 SCP, SCP4🡪 SCP; | Measurement indicators of SCP are not interchangeable amongst each other as indicators that measure SCP. Ex: Indicators used for measuring SC cost cannot be substituted by indicators measuring delivery, flexibility, and quality and vice-versa. | The relative mutual independence among the indicators measuring different dimensions of SCP suggests a weak correlational effect. Indicators measuring SC cost may not necessarily be associated with indicators measuring on -time delivery. | Nomological validity of SCP construct can be evaluated by analysing the significance level of the structural path with its causal and outcome constructs. |
| Supply chain quality (SCP2) |
| On-time delivery (SCP3) |
| Flexibility of the supply chain (SCP4) |

**2.4 Hypotheses development and research framework**

Supply chain operations are growingly becoming vulnerable due to uncertain market conditions (ESCC1). It is primarily caused by the diversity of external factors beyond its control. These often include factors, such as changing geopolitical situation around the globe, trade laws and regulation, change in tax policies, cross-currency (Chand *et al*., 2018). External environmental complexity follows through the firm’s selection and adoption of several operational and manufacturing strategies (Ketokivi 2006). According to Dittfeld *et al*. (2018), in their response to growing external complexity, firms adapt several organizational strategic measures that bring in ‘outside in’ complexities. Thus, ESCC drivers are likely to develop other SCC drivers at multiple levels. Extending the tenets of the contingency perspective, Boyd *et al*. (2012) argued that a complex and dynamic external environment influences most relationships. Change in technology or technological innovation might result into shortened product life cycle with associated dynamic impact on supply chain network (Manuj and Sahin, 2011). Further, increasing global trend of sustainability, outsourcing, emerging market trends have put pressure on firms in adoption of newer technologies and processes (Serdarasan, 2013; Dittfeld *et al.,* 2018). The introduction of new products that are technologically superior (ESCC2) can create competitive pressure on the focal firm in multiple ways. It may necessitate the development of new components/parts, different supplier bases, increased number, and types of SKUs. It seems to impact supply chain performance if not managed adequately (Turner *et al*., 2018). Further, ESCC can also have a significant impact on customer demand. We, therefore, propose:

***Hypothesis 1a:*** *External supply chain complexity (ESCC) influences USCC*

***Hypothesis 1b:*** *External supply chain complexity (ESCC) influences OSCC*

***Hypothesis 1c:*** *External supply chain complexity (ESCC) influences DSCC*

Research findings indicate that long-term strategic relationships with suppliers and logistics integration with supplier-base can significantly positively affect a firm's key operational performance aspects like cost, flexibility, and delivery (Projogo *et al*., 2012). Collaboration with the supplier base positively impacts supply chain delivery performance at the operational level; and enables strategizing a responsive supply chain (Roh *et al*., 2014). Choi and Krause (2006) prove that with the increase in supply base complexity, transactional cost increases and supplier responsiveness reduces. Global sourcing with an extended network of suppliers dispersed at distant geographies results in elongated movement with increased transportation cost coupled with high inventory due to typical long lead time (Golini and Kalchschmidt, 2011). Empirical evidence suggests that there can be a considerable causal influence between USCC with OSCC as an increase in the complexity of the former tends to increase the complexity of the latter two. Therefore, we have theorized the relationship with the following hypothesis.

***Hypothesis 2a:*** *USCC influences OSCC (increase in USCC will result in increase in OSCC).*

The presence of information and knowledge asymmetry in vertical and spatial complexity is likely to impact buyer-supplier collaboration efforts with an outreaching impact on supply chain performance (Lu and Shang, 2017). Horizontal complexity of a firm increases with the addition of suppliers managed by the firm directly. An increase in the number of suppliers in a firm's supply base causes higher information flow higher inter-firm coordination with a greater number of transactions (Choi and Krause, 2006). Supply base complexity (horizontal complexity) is responsible for the increase in the frequency of supply chain disruptions with an adverse impact on plant performance (Brandon-Jones *et al*., 2014). Likewise, with the increase in the number of tiers of suppliers (depth of supplier), the firms are more likely to experience the domino effect (Bode and Wagner, 2015). It is argued that the increase in vertical complexity is responsible for increasing the higher level of uncertainty in the upstream supply chain (Milgate, 2000). Due to the possible presence of information and knowledge asymmetry, it is argued that the increase in vertical and spatial complexity is likely to impact buyer-supplier collaboration with an expansive impact on SCP (Lu and Shang, 2017). Further, global sourcing is also influenced by a 'wide range of complicated factors' due to cross-border laws and regulations, dependence on infrastructural requirements, cultural differences (Bozarth *et al*., 2009). The disruption caused by USCC may adversely impact the downstream supply chain performance of a firm (Birkie and Trucco, 2020). We, therefore, conceptualized the following hypothesis to test the impact of USCC drivers at an individual level on supply chain performance for the manufacturing industry context.

***Hypothesis 2b:*** *Upstream supply chain complexity (USCC) negatively influences SCP.*

Due to the inherent interconnectedness of the supply chain network, any change in OSCC can impact upstream activities (Aitken *et al*., 2016). Growth in part complexity is considered a significant supply chain risk- that potentially can disrupt the functioning of firms due to an increase in inherent risks of part shortages, transportation delay, schedule slippages (Inman and Blumenfeld, 2014). Besides, higher product complexity, referred to as the complex interaction of parts, if not managed comprehensively, may lead to supply chain uncertainties with a considerable negative impact on inventory and logistics cost, resulting in erosion of supply chain competitiveness (Gunasekaran *et al*., 2014). Despite the seeming market advantage of product diversity, excessive product variety can impair SCP by making it 'inflexible and inefficient' (Hoole, 2006). The typical cost associated with managing material flow, transactions, resource engagement, asset conversions emanated from higher product variety entail a greater level of expenditure and negative impact on SCP (Jacobs and Swink, 2011). In summary, we propose:

***Hypothesis 3:*** *Operational supply chain complexity (OSCC) negatively influences SCP.*

Firms tend to accommodate the heterogeneity of customer-specific requirements (DSCC1) to improve the customer base and customer acceptance of their products as a part of business strategy (Aitken *et al*., 2016). The cost of reaching and serving an increased number of customers variety of customer orders with geographical spread usually results in a negative impact on financial profitability measures (Gerschberger and Hohensinn, 2013). Managing a geographically dispersed customer base with greater customization includes creating a deeper distribution network, increased inventory cost, and delayed cash realization cycle (Lorentz *et al*., 2012). Further, the transaction cost will likely increase in serving an increased customer base due to distributed transportation and logistics expense. Additionally, greater customization beyond a certain point might impact the operational efficiencies due to smaller batch sizes and frequent set-up changes (Ates *et al*., 2022). Variability in demand (DSCC2) at the downstream supply chain can significantly amplify the adverse functional impact ('Bullwhip effect') at upstream sources (USCC and OSCC) with severe fluctuations (Bozarth *et al*., 2009). Aitken *et al*. (2016) argued DSCC as the originating point of supply chain complexity, transmitting complexity at operational and upstream directions. Hence, we propose:

***Hypothesis 4a:*** *Downstream supply chain complexity (DSCC) influences USCC.*

***Hypothesis 4b:*** *Downstream supply chain complexity (DSCC) influences OSCC.*

***Hypothesis 4c:*** *Downstream supply chain complexity (DSCC) negatively influences SCP.*

Therefore, the conceptual research model with a related hypothesis is illustrated in Figure 2.

Shape

Description automatically generated with medium confidence

**Figure 2:** Proposed model to measure the impact of SCC) on SCP

**3. Research methodology**

This study investigates the impact of supply chain complexity on supply chain performance (SCP). Based on available literature on SCC, we classified the entire SCC into four major categories, namely, USCC, OSCC, DSCC, and ESCC, which summarily explain SCC. Our research model is structured with five formative constructs USCC, OSCC, DSCC, ESCC, SCP. A total of fourteen indicators represents these constructs, and complex inter-relationship among constructs is theorized with a set of nine (H1a, H1b, H1c, H2a, H2b, H3, H4a, H4b, and H4c) hypotheses.

**3.1 Survey development**

The survey was developed based on the research model (Figure 2) with five main constructs for this study. The indicators applied for measuring constructs in the 'Measurement model' are obtained from existing literature to increase the validity and reliability of the model, as shown in Table 3 (for formative constructs). The structural model was established by linking the exogenous constructs with endogenous. A three-step method was followed in finalizing the structure and content of the survey instrument (Pradabwong *et al*., 2017; Ramkumar and Jenamani, 2015). Firstly, the survey content was assessed for wording and clarity by four selected academicians from Indian premium management institutes with subject matter experience of more than 15 years individually. Next, the survey content was reviewed for verifying the clarity of indicators by five SC industry experts from the industrial manufacturing sector. Subsequently, a pilot survey was conducted involving 25 SC managers from various manufacturing firms for indicator refinement and content validation. Indicators representing the constructs in the measurement model are evaluated on a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). Numeric values of Likert scale are interpreted as, 1 = strongly disagree, 2 = disagree, 3 = somewhat disagree, 4 = neutral, 5 = somewhat agree, 6 = agree, 7 = strongly agree, to indicate the degree of acceptance (Whitten *et al*., 2012).

**3.2 Large-scale data collection**

We collected the large-scale response data through extensive surveys and meetings conducted from December 2018 to June 2020. The SC experts, working in manufacturing industries, were approached through multiple contact links such as company website page, email addresses from professional websites through an extended professional network. The expert responses were collected through a) meeting in person, b) online survey, c) telephonic discussion, d) Industrial and promotional events, and e) discussions during conferences on the related industry. Special efforts were made through phone calls and reminder emails to improve the response rate. The survey was conducted in five major manufacturing clusters geographically distributed around India. We ensured senior management levels (assumed ≥15 years of experience) to ensure a holistic perspective on the subject. SC practitioners' expertise ranged from a minimum of 15 years to a maximum experience of 27 years (Mean experience: 18.2 years; Standard deviation: 6.76 years). The survey statistics are detailed in Table 2.

To assess the quality of the collected response data, non-response bias was measured based on the mean values of indicators with the early respondents (first 37 responses= 15% of the total responses) and the late respondents (last 37 responses=15% of the total responses). 'Paired two Sample *t*-Test for Means' was conducted to evaluate the responses. The results suggested that there was no statistically significant difference between earlier and later responses at a 95% confidence interval (*p* < 0.05) for the selected indicators.

**Table 2:** Sample survey statistics

|  |  |  |
| --- | --- | --- |
| **Demographic characteristics** | **Frequency** | **%** |
| **Response’s collection mode** | 48 | 19.51 |
| In-person meeting |
| Online survey | 116 | 47.15 |
| Telephonic discussion | 12 | 4.88 |
| Industrial and promotional events | 28 | 11.38 |
| Conference/seminars | 42 | 17.07 |
| **Respondent's rank** |  |  |
| Top management | 86 | 35.00 |
| Middle management | 124 | 50.00 |
| Professional consultant | 36 | 15.00 |
| **Respondent’s work experience** |  |  |
| 15-20 years | 158 | 64.00 |
| More than 20 years | 88 | 36.00 |
| **Firm's characteristics** |  |  |
| Number of years of operation |  |  |
| 5-10 years | 14 | 5.69 |
| 10-15 years | 85 | 34.55 |
| 15-20 years | 79 | 32.11 |
| More than 20 years | 68 | 27.64 |
| **Annual turnover of the company** |  |  |
| Less than INR 10 Crore | 12 | 4.88 |
| INR\* 1-100 Crore | 74 | 30.08 |
| INR 100-500 Crore | 56 | 22.76 |
| INR 500-1000 Crore | 96 | 39.02 |
| More than INR 1000 Crore | 8 | 3.25 |
| **Product-wise manufacturing firms** |  |  |
| Mining & Material handling | 41 | 16.67 |
| Industrial equipment | 29 | 11.79 |
| HVAC and allied products | 16 | 6.50 |
| Construction equipment | 12 | 4.88 |
| Farm equipment | 14 | 5.69 |
| Electrical machinery | 26 | 10.57 |
| Automobile and Auto ancillary | 63 | 25.61 |
| Furniture | 27 | 10.98 |
| Home appliances | 18 | 7.32 |

(\*Approximate currency conversion rate: US$1= INR 75; US$ 1 million= INR 7.5 Crore)

**3.3 Data analysis method evaluation**

The study proposes to apply variance-based partial least square-structural equation modelling (PLS-SEM) to compute the total variance for parameter estimation (Hair *et al*., 2016). The current research proposal conforms to the following conditional requirements for selecting a composite-based path network as per PLS-SEM suggested by researchers (Peng and Lai, 2012; Hair *et al*., 2018).

* We intend to explore the nomological network among the theoretical constructs by proposing a hypothesis to test the relationship among the constructs to address the relative scarcity of well-established theory.
* The relationship study is modelled on the predictive power of a set of exogenous constructs on endogenous variables to measure relational strength (Vinzi *et al*., 2010).
* Our research model consists of formatively measured constructs (Hair *et al*., 2014).
* Lack of normality in collected data can also be accommodated through PLS-SEM (Hair *et al*., 2012).
* The research was conducted for the Indian manufacturing industry. As mentioned earlier, the number of available experts on supply chain management in the industry is relatively less due specificity of the industry resulting in a limited sample size.

**3.4 Sample sizes and model complexity**

PLS-SEM enables computation with a smaller sample size for relatively complex models constituted by many constructs associated with many indicators (Hair et al., 2016). The data collection was focused on gathering industry-specific construct relationships contextual to supply chain applications. Therefore, the sample heterogeneity is controlled by imposing a situational-based equality assumption (Rigdon, 2016), facilitating a relatively smaller population size to achieve acceptable sampling error (Hair et al., 2018). Following the conditions of model complexity and lack of heterogeneity, we have applied the "10 times" rule of thumb for sample size estimation as recommended by Peng and Lai (2012). This rule specifies that 'PLS only requires a sample size of 10 times of most complex relationship within the research model'. The most complex relationship applicable to our research model is defined by the value of 'the construct with the largest number of formative indicators' (Peng and Lai, 2012). According to this stipulation, the minimum sample size required to conduct the PLS can be 30 (10 X 4=40). The received responses of 246 are adequately meeting the minimum sample size requirement.

**4. Data analyses and results**

**4.1 Measurement model evaluation**

**Figure 1: Illustrative research model**: To measure the impact of supply chain complexity (SCC) on supply chain performance (SCP)

USCC1

USCC2

USCC3

OSCC1

OSCC2

OSCC3

DSCC 1

DSCC2

ESCC1

ESCC2

Delivery Lead Time (SCP3)

Cost (SCP1)

Quality (SCP2)

CS1

CS2

CS3

MS1

MS2

MS3

Flexibility (SCP4)

H1

H2

H3

H4

H5

H7

H6

H5

Measurement Model

Measurement Model

Measurement Model

Structural Model

We have applied 'partial least square-based structural equation modelling' PLS-SEM) SmartPLS 3.0 (Ringle *et al*. 2014) to determine the validity and reliability of the measurement and structural models to test the proposed hypothesis. We have employed multiple stringent validity and reliability tests for formative constructs at the indicator and construct levels to ensure the measurement model robustness (Peng and Lai, 2012).

**4.2 Measurement properties for formative indicators and constructs**

First, for formative constructs, examining the multicollinearity of formative indicators is essential to check the redundancy of the indicators. Multi-collinearity of indicators is ascertained by calculating the Variance Inflation Factor (VIF), where a VIF value less than 3 suggests the absence of multicollinearity (Hair *et al*., 2011). Secondly, the importance of formative indicators is assessed with their corresponding weights contributing to formative constructs, as formative constructs are aggregately represented by respective indicators weight and magnitude (Götz *et al*., 2010). The formative indicators' importance is measured by their 'outer weight' in SmartPLS, and indicator values not less than 0.1 are considered statistically significant (Andreev *et al*., 2010). Finally, the content validity of the indicator is already checked during the evaluation of survey instruction, as mentioned in section 3.2. The measurement properties of formative indicators and constructs are summarized in Table 3. VIF values for indicators, except OSCC4, are less than 3 suggesting the absence of multicollinearity. All the outer weights of indicators at the individual level, except DSCC1, are more than the minimum threshold value of 0.1, advocating statistical significance in contributing to the construct. Therefore, indicators OSCC4 and DSCC1 are dropped from further evaluation and will not be part of the structural equation model.

**Table 3:** Measurement properties of formative constructs

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Construct | Indicator (label) | Item Loading | t-Stat. | VIF |
| Upstream supply chain complexity (USCC) | Our firm manages and controls the total number of direct suppliers (USCC1) | 0.358 | 2.438 | 1.145 |
| Our firm manages multiple tiers of suppliers (USCC2) | 0.204 | 1.663 | 1.254 |
| Our suppliers are geographically widespread (USCC3) | 0.723 | 5.679 | 1.227 |
| Operational supply chain complexity (OSCC) | The management emphasizes on restricting the total types of parts (OSCC1) | 0.736 | 6.618 | 1.195 |
| The management encourages to maintain required product variety (OSCC2) | 0.408 | 3.003 | 1.071 |
| The management recommends standardized processes (OSCC3) | 0.183 | 1.384 | 1.212 |
| Our firm manages product life cycle efficiently (OSCC4) | 0.346 | 2.325 | 4.434 |
| Downstream supply chain complexity (DSCC) | Our firm is adept in managing increased number of customer orders (DSCC1) | 0.086 | 2.215 | 2.324 |
| Our firm accommodates the variety of customer-specific product features (DSCC2) | 0.415 | 0.664 | 1.069 |
| The management is committed in executing orders variability from customers (DSCC3) | 0.810 | 1.460 | 1.069 |
| External supply chain complexity (ESCC) | The management acknowledges the uncertainty in the market as a potential disruptor to supply chain (ESCC1) | 0.953 | 2.174 | 1.048 |
| The management recognizes technological disruption can impact internal and external supply chain (ESCC2) | 0.569 | 1.308 | 1.048 |
| Supply chain performance (SCP) | Our firm is measuring supply chain cost volume ratio (SCCR) for all supply chain processes (SC1) for comparative time. | 0.500 | 3.025 | 1.365 |
| Firm's supply chain quality is measured as percentage of accurately specified goods delivered to customers conforming to product and service quality as per customer requirement (SCP2). | 0.354 | 1.550 | 1.781 |
| Our company is measuring the on-time delivery performance as a percentage of orders delivered on or before the due date (SCP3) | 0.239 | 1.249 | 1.668 |
| Our firm is flexible in managing number and variety of product modifications which are accomplished without incurring high transition penalties or large changes in performance outcomes’ (SCP4) | 0.200 | 1.217 | 1.484 |

At the construct level, we have conducted a discriminant validity test and nomological validity test. The discriminant validity confirms that the indicators of a formative construct should have the strongest relationships with that construct in comparison with any other constructs (Hair *et al*., 2016). The discriminant validity for the formative constructs is established through cross-loadings analysis as shown in Table 4. Nomological validity is confirmed through path co-efficient (*T*-statistics check for significance) of USCC and OSCC.

**Table 4:** Cross Loadings of Items

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Items | DSCC | ESCC | OSCC | SCP | USCC |
| DSCC2 | **0.722** | 0.040 | 0.006 | 0.093 | 0.064 |
| DSCC3 | **0.853** | -0.187 | 0.167 | 0.110 | 0.058 |
| ESCC1 | 0.278 | **0.873** | 0.104 | 0.171 | 0.209 |
| ESCC2 | 0.321 | **0.290** | 0.193 | 0.057 | 0.033 |
| OSCC1 | 0.068 | 0.100 | **0.884** | -0.688 | 0.626 |
| OSCC2 | 0.066 | 0.211 | **0.600** | -0.504 | 0.367 |
| OSCC3 | 0.244 | 0.202 | **0.567** | -0.385 | 0.449 |
| SCP1 | 0.086 | 0.151 | -0.634 | **0.794** | -0.529 |
| SCP2 | 0.198 | 0.197 | -0.622 | **0.865** | -0.681 |
| SCP3 | 0.025 | 0.078 | -0.524 | **0.695** | -0.555 |
| SCP4 | -0.005 | 0.136 | -0.542 | **0.643** | -0.456 |
| USCC1 | 0.006 | 0.214 | 0.409 | -0.478 | **0.622** |
| USCC2 | 0.074 | -0.008 | 0.428 | -0.432 | **0.601** |
| USCC3 | 0.810 | 0.202 | 0.636 | -0.661 | **0.906** |

\*(Note. Factor loadings are shown in bold)

**4.3 Structural model estimation**

We run the model using SmartPLS3.0 bootstrapping for structural model estimation to test the significance of the path relationships repeated with 2000, 2500, and 3000 times of resampling. Increasing the number of sampling iterations in the Bootstrapping process diminishes the erroneous effect of random sampling. Bootstrapping provides 'estimation of standard errors and significance of parameter estimates' (Peng and Lai., 2012). The path-coefficient and *t*-statistics values remained consistent for 246 test samples with resampling repetition. The path coefficients and *T*-statistic values are used to determine the significance of structural model relationships proposed through the hypotheses. While the magnitude of the path coefficients signifies the extent of the causal relations between constructs, the sign represents a positive/negative direction. Due to the directionality of our conceptualized hypothesis, a one-tailed t-test is appropriately justified to check the significance of causality. The statistical test results computed through bootstrapping include path-efficient, *t-*test values of the causal path, associated *p* values, and hypothesis status as shown in Table 5 and represented in Figure 3.

**Table 5:** Results of the Structural Model

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Hypothesis** | **Path** | **β-Coefficient** | **S.D.** | ***t* statistics** | **Status** |
| H1a | ESCC→USCC | 0.541\*\* | 0.126 | 6.276 | Supported |
| H1b | ESCC→OSCC | 0.327\* | 0.102 | 3.192 | Supported |
| H1c | ESCC→DSCC | 0.612\*\* | 0.072 | 8.923 | Supported |
| H2a | USCC→OSCC | 0.693\*\* | 0.068 | 10.262 | Supported |
| H2b | USCC→SCP | -0.375\* | 0.149 | 2.512 | Supported |
| H3 | OSCC→SCP | -0.506\*\* | 0.145 | 3.501 | Supported |
| H4a | DSCC→USCC | 0.023 | 0.108 | 0.215 | Not supported |
| H4b | DSCC→OSCC | 0.265\* | 0.056 | 2.724 | Supported |
| H4c | DSCC→SCP | 0.007 | 0.101 | 0.069 | Not supported |

\*\**p* < 0.05 (significance at 0.05 level), \**p* < 0.10 (significance at 0.10 level)

Shape

Description automatically generated with medium confidence

**Figure 3:** **Notes:** \*\**p* < 0.05 (significance at 0.05 level), \**p* < 0.10 (significance at 0.10 level)

**4.4 Structural model assessment**

The explained variance is measured by the coefficient of determination (*R2*) of the endogenous constructs present in a model and signifies the model's explanatory power (Shmueli and Koppius, 2011). The value of *R2*ranges between 0 to 1 with the higher value explains greater model explanatory power (Hair *et al*., 2019). Researchers have also highlighted *R2* as the predictive power of the sample (Rigdon, 2012), and the model's predictive accuracy (Hair *et al*., 2014). The computed values of *R2* for the endogenous constructs USCC, OSCC, DSCC, and SCP are 0.542, 0.480, 0.352, and 0.669. The research model, with SCP as a prime endogenous effected construct with *R2* equalling to 0.669, can be termed as satisfactory (Pradabwong *et al*., 2017) as the value of *R2* records within the pivotal values of 0.75 (substantial) and 0.5 (moderate) (Hair *et al*., 2019).

Another important measure to examine the model's predictive relevance is Stone-Geisser's *Q2* values, which is obtained through the 'Blindfolding' process in SmartPLS (Chin, 1998). As per measurement guidelines by Hair *et al*. (2019) on *Q2*, higher values indicate superior predictive accuracy. *Q2* value, which is more than 0.25, is considered to have medium predictive relevance of the model. With the obtained values of *R2* (= 0.669) and *Q2* (= 0.349) of SCP, it can be surmised that the research model exhibits sufficient explanatory influence in estimating the impact of the supply chain complexity on SCP for inferential decision-making. From the obtained results of explained variance (*R2* = 0.669 and *Q2* = 0.349), it can be surmised that SCP is influenced by up to 66.9% by a combination of USCC, OSCC, and DSCC constructs. It can, therefore, also be inferred that other factor which are beyond the scope of this research, have a remaining impact (by 33.10%) on SCP. Stone–Geisser's *Q2* for endogenous constructs USCC, OSCC, DSCC and SCP are 0.312, 0.216, 0.122, and 0.349, respectively. The result demonstrates an acceptable predictive model accuracy.

**4.5 Mediation effects**

We conduct a mediation effect analysis for precise comprehension of the causal impact of constructs explained in research design (Ramkumar and Jenamani, 2015). It is conditional to the fulfilment of the following preconditions, (1) the direct relationship without mediation effect should be statistically significant; (2) the indirect effect post mediation should also be statistically significant; and (3) If the variance accounted for (VAF) is greater than 80%, it represents full mediation, 20% ≤ VAF ≤ 80% means partial mediation and VAF<20% indicates there is no mediation effect.

Analysis of mediation effect shows the presence of important mediating paths which are statistically significant. Mediation effects as represented by paths ESCC→USCC→SCP (indirect effect size: *β* = - 0.092, *t* = 2.216, VAF = 67.2%), ESCC→OSCC→SCP (indirect effect size: *β* = - 0.078, *t* = 1.912, VAF = 77.6%), ESCC→DSCC→SCP (indirect effect size: *β* = - 0.112, *t* = 2.342, VAF = 56%) and USCC→OSCC→SCP (indirect effect size: *β* = - 0.351, *t* = 3.159, VAF=48.3%) are statistically significant with the presence of partial mediation. The mediating effects, analysed path-wise, are sufficing the afore-said three conditionalities.

**5. Discussion and managerial implication**

**5.1 Discussion of results**

The current research investigates the hitherto unexplored complex interactions among multiple drivers of SCC and SCP. The construct of SCC is conceptualized as a combined representation of four constituent constructs denoted as USCC, OSCC, and DSCC, externally affected by ESCC. We theorized the constructs (USCC, OSCC, DSCC, ESCC, SCP) on a formative scale and measured them by causal formative indicators (Nunnally and Bernstein, 1994). The breadth of the construct representation is ensured through extensive content validity by literature review, panel discussion, and expert interview (Andreev *et al*., 2009). While most research findings show consistency with prior research postulates, some outcomes differ from conventional theory.

First, the research model establishes the strong positive causal effect of ESCC on USCC, OSCC, and DSCC (hypothesis H1a, H1b, and H1c). External complexity can have a meaningful impact at all levels of SCC (USCC, OSCC, DSCC) experienced by the firm. Thus, we strengthen the conceptualization of SCC as complex and emergent system with interacting elements (Manuj and Sahin, 2011). This observation distantly supports the ‘outside in’ proposition of Dittfeld *et al*. (2018), reasoning external complexity as probable origination for multiple SCC. Our work elaborates on the multidimensional concept of SCC and investigates the direct and mediated impact of individual constructs on SCP (Ateş *et al*., 2022).

Second, from the resulting outcome, it is evident that USCC and OSCC cause a significant adverse effect on SCP as hypothesized in H2b and H3, respectively (Kavilal *et al*., 2017). However, DSCC fails to provide enough support in affecting SCP. This finding contradicts previous research findings, which argues the impact of downstream complexity on a firm’s performance (Bozarth *et al*., 2009; Vollmann *et al*., 2005). However, this outcome remotely corresponds with the proposition that DSCC generated by the customer may not necessarily reduce performance (Aitken *et al*., 2016; Wiengarten *et al*., 2017). With a growing orientation towards customers, firms might be strategically prepared to deal with downstream complexities- making the investment to increase a deeper dealership network to serve a larger customer base (DSCC1). Highlighting the importance of dealership reach, Associate Vice President, Marketing & Business Development of a farm equipment company commented, “We strongly believe our dealership as a business partner and strategic strength for our business. We are extensively building dealers to have larger geographical reach to be able to serve the increasing number of customers in a more timely manner.” Dealers are often better connected to customers than firms, enabling firms to customize products (DSCC2) based on market requirements (Fites 1996). Besides, early engagement with customers in product development might help firms in product features and innovation management (Ates *et al*., 2022). Understanding customers better can support creating higher value for the customer through tailor-made offerings (Porter and Heppelmann, 2015). The downstream supply chain structure of the manufacturing sector involves three key stakeholders: manufacturer, dealer, and the customer. The growing adoption of information-technology enabled products and services might have enabled firms to remain connected with customers. Integration of downstream supply chain stakeholders (ref: Figure 1), connected to the real-time information-sharing system, can reduce the information flow asymmetry-demand variability (DSCC3) (often referred to as ‘Bullwhip Effect’) (Yao and Zhu, 2012).

Third, it is noteworthy that ESCC will indirectly impact SCP mediated through USCC, OSCC, and DSCC simultaneously (Section 4.5). This finding is distantly coherent with Turner *et al*. (2018), who suggests multiple simultaneous presences of external and internal complexity dimensions of the supply chain in project management that can have an impact on overall performance. The model demonstrates the interaction between USCC and OSCC constructs, with USCC positively impacting the OSCC (H2a). The partial mediating impact of OSCC is supported by 48.3% of the total effect size. It also suggests that the USCC has a negative causal relationship with SCP (H2b) (Bode and Wagner, 2015) and a mediated relation through OSCC. The combined explained variance of SCP caused by USCC and OSCC is more than the explained variance caused by USCC and OSCC individually. This outcome confirms the presence of ‘amplifying or super-additive interaction’ of USCC and OSCC impacting SCP. This finding stands by the ‘non-linear’ proposition of SCC, represented by interaction effect among drivers (Dittfeld *et al*., 2018), rather than being a ‘cumulative concept’. Hence, concentrating merely on the direct effect relations may provide only a partial explanation of the effect. While we acknowledge the importance of direct relationship, indirect/mediated inter-relationship offers comprehensiveness in explaining relational complexity (Boyd *et al*., 2012).

Fourth, surprisingly, DSCC does not exhibit a significant direct effect on USCC (H4a). However, it shows the meaningful impact on OSCC (H4b). While the later observation (H4b: DSCC🡪 OSCC) is in alignment with Aitken *et al*. (2016), the results differ in the former (H4a: DSCC🡪 USCC). This suggests that downstream complexity generated by increasing customer base (DSCC1), product customization need (DSCC2), and demand variability (DSCC3) may not result in increasing upstream complexity meaningfully. Although the changes in downstream SCC will ‘reverberate’ through the operational SCC changes at the firm level, this may not get sufficiently passed to USCC. Extending the same, the focal firm tends to act as ‘decoupling agent’ in transmitting the downstream complexities to upstream. If this deems correct, then a large part of the downstream complexity management is being controlled and managed by the nodal firm within the purview of its operation (Serdarasan, 2013). This connects us back to the concept of complexity ‘absorption’ and/or ‘reduction’ strategy adopted by the firms (Aitken *et al*., 2016).

Finally, the coefficient of determination (*R2*) value of 0.669 for the salient endogenous construct SCP indicates the sufficiency of the model’s explanatory power. The model’s predictive relevance as measured by Stone-Geisser’s *Q2* value (for SCP, *Q2*=0.349) ensures acceptable predictive model accuracy. The combination of *R2* and *Q2* values satisfy the robustness of the model. The outcome enriches ongoing research with following theoretical and managerial implications.

**5.2 Theoretical implications**

The key research question we wanted to answer is "Why and how do supply chain complexity drivers impact the supply chain performance in the presence of complex interactions?". Several past studies explored the relationship among SCC drivers at the individual interaction level (Dittfeld *et al*., 2018). This research investigates the complex intervening relationships among SCC drivers in the presence of ‘*simultaneous interactions’*. Therefore, our research findings fill the yet unexplored research gap that ignores the effect of simultaneous interactions in SCC. To this end, we enrich the theoretical understanding that explains complex simultaneous interactions among SCC drivers beyond direct effects. Further, this study explored the direct and mediated effect of the SCC drivers, individually and combinedly, on SCP. In doing so, we address an important research limitation seeking due attention (Ates *et al*., 2022). The empirical model explains the distinctive effect of SCC drivers on SCP with sufficient explanatory power.

Second, methodologically, using a large sample size provides the statistical generalisation of the findings. In this regard, the result offers a quantified assessment of the relationship signifying the extent of the interaction effect. Hence, this study overcomes the limitation associated with empirical studies with the fewer dataset (Aitken *et al*., 2016). While some prior studies proposed the interaction of SCC as non-linear, we quantitatively capture the effect. Thus, the outcome can be more precise with quantitative exactness of non-linear interaction. The quantitative validation can guide in estimating the resultant change in the model caused by a one-unit change in the source construct (Sharma *et al*., 2020). In elaborating on the magnitude of the relationship, we contribute to the discussion on how firms can gain by managing various SCC (Menezes *et al*., 2021). Our findings shed light on the simultaneous interactions of SCC, specifically for the manufacturing industry. Hence the results might expand the theoretical understanding of earlier studies, as interactions among SCC can be context-specific (Dittfeld *et al*., 2018). Additionally, contextual to a different industry, the research outcome provides the basis for comparable theoretical validation with upcoming future studies.

Third, we further the theoretical understanding of SCC drivers with the multi-dimensional conceptualisation of constructs and their relationship with SCP. By doing so, our study complements the ongoing academic discourse of SCC in explaining interactions, which seemingly lacks theoretical underpinning (Ateş *et al*., 2022). The inclusion of ESCC in the structural model provides a unique perspective in analysing the problem, including externalities and limited contingencies (Wiengarten *et al*., 2017). Tellingly, the vital role of ESCC with the direct effect on USCC, OSCC, DSCC, and mediated effect on SCP offers distinction to this research. Changes in ESCC is likely to cause a resulting impact on SCP, mediated through a complex network involving USCC, OSCC, and DSCC. We found interconnected non-cumulative relational behaviour among the constructs of SCC and SCP, positioned as networked nodes of a complex system (Figure 2). This finding corresponds to the organisational complexity perspective (Choi *et al*., 2001).

Fourth, this study theorizes the SCC and SCP constructs on a formative scale with constructs being formed using formative indicators. The conceptualization of formative indicators in measuring constructs are sufficiently reasoned (ref: Table 1). This captures the additive impact of indicators (representing detail and dynamic aspects) corresponding to the respective construct. The application of formative scale in structuring the constructs might offer greater inclusiveness to the constructs. To that end, our study may fulfil the conceptual need in making constructs more inclusive (Wiengarten *et al*., 2017). This approach adds methodological uniqueness for measuring SCC and SCP. Besides, the current research design (use of formative scale) complements the existing research of SCC, being represented in reflective scale (Bozarth *et al*., 2009) and numeric scale (Bode *et al*., 2015). We propose that due to the formative nature of the indicators (without significant covariance among them), managing and controlling complexity at the indicator level will have a corresponding impact on the construct (Thomé and Sousa, 2016). To illustrate this point further, analysis of the outer weights of the indicators of OSCC indicates that part complexity (OSCC1) has a more significant impact in forming the OSCC construct compared to product complexity (OSCC2) and process complexity (OSCC3). We find this observation theoretically supportive of Wan and Sanders (2017) research outcome, who inferred that increase in product variety often drives growth in the number of SKUs (parts), resulting in higher inventory.

**5.3 Managerial implications**

For effective SCP management, it is imperative that supply chain managers control and monitor the SCC. Knowing the effect of SCC drivers among themselves and on SCP will facilitate the SC managers in devising the right strategies, which is scarce in the literature. We propose the following insights for practitioners to enable policy recommendations. First, ESCC is likely to have a corresponding impact on other drivers of SCC (USCC, OSCC, and DSCC). Therefore, effective management of ESCC might result favourably in managing other SCC drivers. ESCC drivers, which are typically beyond the control of focal firms, are relatively difficult to manage for the firms (Ateş *et al*., 2022). ESCC, primarily driven by market uncertainty, globalized economic disruption, currency exchange fluctuations, cyclicity of market growth, and geopolitical events, may significantly increase overall SCC. Hence, supply chain decision-makers might pay more attention to ESCC at the firms’ organizational design level (Dittfeld *et al*., 2018). As part of corporate strategy, to control the ESCC drivers, many global corporations are expanding their manufacturing footprint in multiple geographies- to avoid being adversely affected by any externalities of the supply chain. For example, Hitachi has expanded its overseas business at various locations around the globe, driven primarily by ESCC drivers. The imposition of anti-dumping duties by the European Community (resulted in Fiat-Hitachi JV in Europe and subsequently manufacturing unit by Hitachi in Amsterdam), the adverse exchange rate of Yen against US Dollar (Deere-Hitachi JV and Euclid-Hitachi JV in the US with plants located at the US), uncertainty on tariff and tax-related risks (Russia and Brazil) are some prominent examples (Takatani *et al*., 2015). A geographically distributed manufacturing presence might act as one of the strategic levers in controlling the adverse impact of ESCC.

Second, the firm should focus on decreasing USCC by reducing formative drivers of the same, such as horizontal SCC (USCC1), vertical SCC (USCC2), and spatial SCC (USCC3) individually and/or combinedly. Supply chain managers should reduce the supplier base's geographical spread to gain maximum benefit from SCP. Global sourcing of parts and components is commonly attributed to causing the distributed network of suppliers, which tends to complicate the structure of the supply chain (Bode and Wagner, 2015). The extended network of suppliers usually results in elongated material flow, multi-modal handling, longer lead time, dependence on the availability of infrastructure facilities with higher uncertainty (Wagner and Bode, 2006). Our hypothesis finds support in supply chain strategies adopted by leading global manufacturers and suppliers with a significant operating presence in India in managing upstream SCC. Specifically, to limit the impact of spatial SCC (USCC3), many global corporations are driving the initiative to develop the supplier base geographically closer to manufacturing facilities. JCB, a leading global mining and construction equipment manufacturer headquartered in the UK, has developed a significant supplier base in India over the years as a part of supplier development and localization initiative. The company has worked collaboratively with its supplier clusters near its manufacturing plant location by capacity building and improving processes (Economic Times)[[1]](#footnote-1). Experiencing the growing demand for hydraulic excavators in India, Kawasaki Heavy Industries set-up new manufacturing unit for supply of hydraulic equipment by being geographically closer to its customers. This will likely enable Kawasaki to respond more flexibly to its customers’ varying production volumes (Kawasaki newsroom, 2019)[[2]](#footnote-2). To manage vertical SCC (USCC2), Caterpillar Inc[[3]](#footnote-3) is implementing a digital technology-enabled service platform to link its suppliers in creating deeper visibility and managing variability in SCP. Our research findings can be applied in supply chain resource-orientation towards reducing the upstream SCC. Measures such as supplier base reduction, vertical integration, and development of suppliers nearby to factory location are commonly adopted initiatives.

Third, USCC has a dual advantage in managing SCP, as it directly impacts SCP and indirectly affects SCP mediating through OSCC. Inferring from our result on the outer weights of OSCC indicators, it would be prudent for SC managers to control part complexity. Part complexity is often caused due to multiple factors, such as increased level of customization, the higher number of product variants, lack of standardization, etc. It is often blamed for firms’ negative performance (Salvador *et al*., 2002). It can be controlled through design standardization to enhance parts commonality, restricting the level of customization. Our findings established that USCC has a strong positive causal impact on OSCC. Besides, reducing USCC efficiently can considerably affect the diminution of OSCC. The strong buyer-supplier relationship between Komatsu and Toyo through early-stage engagement in product design corroborates our hypothesis. This strategic collaboration at the sourcing level has a mutually beneficial impact on operational complexity through ‘increased parts commonality across all the firm’s products’ and ‘lowers overall cost’ (Cooper & Slagmulder, 2004).

Additionally, reducing DSCC might result in lowering OSCC. Presently, downstream supply chain networks involve stakeholders of firms, dealerships, and customers (ref: Figure 1). Firms are growingly connected to the real-time information-sharing system to reduce the DSCC. The increasing adoption of technology-enabled products and services enables firms to remain connected with customers in offering greater customization by simplifying (Porter and Heppelmann, 2015). This helps in improving operational and supply chain performance. Therefore, managerial steps should be taken to control formative indicators of DSCC, such as demand variability level of customer-specific product features, among others. It can effectively aid in lessening OSCC by way of types of SKUs handled, resource requirements to manage operations. For example, to manage DSCC effectively, a leading industrial equipment manufacturer has integrated its products/equipment with ‘Equipment Management System’ supported by in-built telematics. This enables in absorbing real-time data on operational SC aspects, such as product utilization, customer demand, better inventory management for spare parts, schedule attainment, and service requirement.

**6. Conclusion**

While researchers have extensively studied the context of SCC and SCP, the critical question: ‘"Why and how supply chain complexity impacts the supply chain performance in the presence of complex interactions?" remains largely unattended in the empirical literature (Ateş *et al*., 2022). This study enriches literature in four meaningful ways. We develop a theoretical framework by systematically examining the impact of various SCC drivers on SCP in a direct and mediated manner. The obtained result provides a context for direct and interacted effects among different SCC drivers. This study offers a basis with the representative model of the manufacturing industry in furthering the understanding of SCC and SCP. Present research advances the ongoing theory of SCC by including external factors through ESCC in the research model.

Despite several significant contributions, we must acknowledge the inevitable limitations of this study. First, the input data was collected involving respondents responsible for managing SC operations; therefore, the result reflects the firms’ internal outlook. The inclusion of respondents from associated upstream and downstream firms might provide a more comprehensive observation. Second, we researched manufacturing firms operating in India. The robustness of the research model can be verified by extending the research problem to other emerging countries/geographies exhibiting similar economic growth to India. The SCC complexity drivers are developed as formative due to their multidimensionality. While the present study adopted a variance-based approach using PLS-SEM, covariance-based SEM will be an exciting area for further theoretical development. Fourth, the study was conducted before the emergence of the Covid-19 pandemic. Hence, the impact of pandemics on SCC drivers and their impact on SCP is beyond the scope of this study. Future studies can investigate the effect of a pandemic on the suggested interaction among SCC drivers and their relationship with SCP. The financial implication of SCC on SCP is beyond the scope of this research. Researchers may explore the interaction effect of SCC drivers on the financial performance of firms.

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